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ARTICLE

Prepared for work in Industry 4.0? Modelling the target activity system and five dimensions of worker readiness

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ABSTRACT

Within Industry 4.0 research, the spotlight shines on technological and organisational challenges. This study shifts the focus to worker readiness, beginning with an analysis of twenty-three models to establish the state of research. Findings demonstrate that existing models are mostly early-stage proposals addressing competences featured in mainstream 21st-century and digital-competence frameworks. Worker-level factors explicitly aligned with emerging cyber-physical systems receive little attention. To construct a worker-readiness model calibrated to the needs of Industry 4.0, the authors devised a research procedure based on a two-phase integrative review of 135 publications. Firstly, they deployed an activity-system apparatus to produce a structured description of the target environment. Secondly, major worker competence groupings, aligned with this target, were extracted, tagged and reduced to five dimensions. The resulting model consolidates prior research and introduces two original competence groupings addressing human-machine partnering and decision-making in Industry 4.0. This study is a foundational step by the Educational Informatics Lab, Ontario Tech University, Canada, toward deploying a global online profile tool for generating, analysing and aggregating worker readiness profiles. This cross-disciplinary project will help researchers, educators, corporate trainers, human resource managers, policymakers, and systems designers more effectively diagnose the readiness of workers for Industry 4.0.

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1. Introduction

The digitalisation of industry is advancing steadily. Catalysed by international programs like Industry 4.0, academics, governments, and private companies are collaborating to reinvent manufacturing. Industry 4.0 is an established global innovation program aimed at making manufacturing facilities more intelligent, efficient and flexible (Orellana and Torres 2019). However, there are different views of Industry 4.0 among small- and medium-sized enterprises (Da Silva et al. 2019) and ongoing challenges producing a roadmap for its full realisation (Liao et al. 2017). Indeed, leading German companies are still working toward advanced stages of maturity (Bittighofer et al. 2018). Given the complexity and scope of industrial digitalisation, much of the academic research focuses on technological and organisational problems. Addressing 'human factors,' and in particular, conceptualising and measuring human readiness for digitalised work receives less attention, and remains an early-stage project (Shahlaei, Rangraz, and Stenmark 2017; Peruzzini, Grandi, and Pellicciari 2020). Nevertheless, this project is crucial to the success of Industry 4.0 because aside from a few 'dark factory' scenarios (Oztemel and Gursev 2018), humans are considered more adaptive than machine entities and vital to future production (Leineweber et al. 2018; Ghobakhloo 2018).

To date, researchers have studied work transformations in digitalised industries from several perspectives. For example, economists have assessed the impact of automation on jobs (Frey and Osborne 2017; Autor 2015), and industrial management specialists have proposed strategies for realigning organisational resources, including personnel, with digitalised manufacturing models (Mittal et al. 2018; Pessl, Sabrina Romina, and Mayer 2017). At the worker level of analysis, the literature offers seminal case studies (Johansson 2017), industry reports (Canadian Apprenticeship Forum 2018), conceptual explorations (Karacay 2018; Romero et al. 2016a) and empirical analyses (Richert 2018). Most importantly, researchers have begun producing new competence models as foundations for Industry 4.0 worker development (Erol et al. 2016; Galaske et al. 2017). With few

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exceptions (van Deursen and Mossberger 2018; Blayone et al. 2020), however, specialised digital-competence researchers have not explored the ability requirements of digitalised industrial work. Instead, they have investigated mainstream digital competences of students and citizens from operator-tool perspectives misaligned with intelligent systems and new forms of human-machine partnering (van Deursen, Helsper, and Eynon 2016; Ferrari 2013; Eshet 2012; Blayone et al. 2018c).

This study bridges this divide and contributes to the advancement of Industry 4.0 readiness research at the worker level. It begins by establishing the state of research through a systematic review of 23 prior readiness models. Then, a new model is constructed from the literature via a two-stage research synthesis to consolidate previous efforts and address significant research gaps. In stage one, the salient characteristics of Industry 4.0 work environments are modelled as an activity-system. In stage two, major competence groupings aligned with these systems are synthesised, and an original five-dimensional model of worker readiness for Industry 4.0 is proposed. This model is a necessary *first step* by the Educational Informatics Lab (EILAB), Ontario Tech University, Canada toward implementing an online application for generating and aggregating Industry 4.0 readiness profiles of individuals around the globe, supporting self-diagnosis and ongoing research to inform higher education, employee (re)training, human resource management and policymaking. Having already implemented a global readiness application for measuring the digital competences of students, teachers and knowledge professionals (Blayone 2018; Blayone et al. 2018a, 2018b, 2018c), this project pivots to the development needs of industrial workers and the requirements of digitalised manufacturing.

2. Establishing the state of research

At the individual and group level, readiness research has roots in learning psychology and technology-systems development (Thorndike 1932; Sullivan 1970). The common goal is to identify and measure *factors* enabling successful human functioning within a *target* context. Factors of interest most often include knowledge, skills, attitudes (KSAs) and related dispositions, which may be grouped as competences (Hoffmann 1999). These are ability complexes that individuals can develop through experience and learning. Situational, cultural and personality factors, though less widely studied, may also be considered, particularly as mediating and moderating variables.

Twenty-three readiness models addressing the needs of workers in Industry 4.0 were selected and reviewed to establish the state of research. They are presented in two groups, featuring thirteen models developed from an organisational perspective, which address workers as a collective entity (e.g. 'workforce' or 'human resources'), and ten from a worker-level perspective. Each model was reduced to a tabular data set to identify common foci, key differences and research gaps. This data set included specified model type, derivation methodology, conceptual readiness structures, human readiness factors, and available instrumentation. The availability of instrumentation was used as a general indicator of a model's maturity because successful operationalisation via the development and validation of a self-report or expert-based assessment tool requires several stages of research beyond initial theorisation.

2.1. Organisation-level readiness models

Key findings from thirteen organisation-level models, shown in Table 1, are as follows. Firstly, these models use 'readiness' and 'maturity' interchangeably as descriptors, even though some studies distinguish between preparation for an initial implementation (readiness) and subsequent development (maturity) (Akdil, Ustundag, and Cevikcan 2018; Botha 2018). Secondly, about half of the models were based on small-scale literature reviews and first-hand theorisations. Others incorporated organisational surveys, interviews with managers, expert processes and assessment frameworks adapted from software development and IT. Thirdly, conceptual structures are diverse, but they position the performance capacities of workers as a critical facet or sub-facet of organisational preparedness. Fourthly, although most models address human readiness generally (1, 3–8 and 13), the rest mention specific worker-level factors, including technology/IT skills (9 and 10), social competences (11 and 12) and intrapersonal dispositions (2). Finally, six studies (1, 3, 9, 11,12 and 13) have produced instrumentation in the form of a survey instrument, checklist or interview guide, but reliability and validity testing is either not reported or planned as next-stage research.

Table 1. Organisation-level Industry 4.0 readiness models compared.

#	Source	Model Type	Method	Conceptual Structure	Human Factor(s)	Instrument?
1	(Akdil, Ustundag, and Cevikcan 2018)	Industry 4.0 Maturity	Small-scale literature review	Three Aspects: Smart Products and Services; Smart Business Processes; Strategy and Organisation. Four Maturity Levels: Absence; Existence; Survival; Maturity	General: Human resources	Yes. Validity and reliability not addressed
2	(Botha 2018)	Future Readiness	Theorised on a future-thinking framework	Three Aspects: Technology; Behaviour; Future thinking.9Five to ten readiness levels in each dimension.)	Specific: Human-machine harmony; Liberated approach to work; Willingness to re-skill; Embrace sharing culture	No. Conceptual structure validated by surveying experts
3	(Canetta, Barni, and Montini 2018)	Digitalisation maturity, with a focus on workers and working conditions	Based on a comparative review of 27 models and interviews	Four Aspects: Processes; Impact; Technology and Human Resources; Technological Process Assessment. Four Maturity Levels: Absence; Novice; Intermediate; Expert	General: Human resource requirement;, Changes in worker skills owing to the digitalisation	Yes. Five-part questionnaire (36 items). Validity and reliability not addressed
4	(De Carolis et al. 2017)	Digital Readiness Assessment Maturity Model (DREAMY)	Capability Maturity Model Integration framework. Literature review and expert input	Four Aspects: Process; Monitoring and Control; Technology; Organisation. Five Maturity Levels: Initial; Managed; Defined; Integrated and Interoperable; Digital-oriented	General: Worker skills to be added to this modular framework (De Carolis et al. 2017)	Unknown. Mentioned but neither described nor provided
5	(Ganzarain and Errasti 2016)	Industry 4.0 maturity model for business diversification towards Industry 4.0.	Theoretical proposal without a formal methodology	Three Stages: Envision; Enable; Enact. Five Maturity Levels: Initial; Managed; Defined; Transform; Detailed Business Model	General: Employeetraining	No. Visual model only
6	(Geissbauer, Vedso, and Schrauf 2015)	PcW Maturity Model for manufacturing managers to assess Industry 4.0 maturity.	Based on a survey involving 2000 + respondents from nine industrial sectors in 26 countries	Seven Aspects: Digital Business Models; Digitisation Offerings; Data and Analytics; Agile IT Infrastructure; Compliance; Security, Legal and Tax; Organisation (Including Employees and Culture). Four Maturity Levels: Digital Novice, Vertical Integrator, Horizontal Collaborator, Digital Champion	General: Worker capacities; Organisation's digital culture	No. Although based on survey research, instrument not published
7	(Gökalp, Şener, and Eren 2017)	SPICE Maturity Model to assess Industry 4.0 maturity.	Small-scale review of models. Software Process Improvement and Capability Determination framework.	Five Aspects: Asset Management; Data governance; Application Management; Process Transformation, Organisational Alignment. Six Maturity Stages: Incomplete; Performed; Managed; Established; Predictable; Optimising	General: Skills of IT personnel; Other human resource requirements for Industry 4.0 transformation	No
8	(Leineweber et al. 2018)	Industry 4.0 migration model to help manufacturing production environments mature.	Based on definitional analysis from the literature, from a socio-technical perspective	Three Aspects: Technological (machine data acquisition, maintenance, data evaluation); Organisational (security, personnel deployment and capacity data); Personnel (expertise, development/ qualification). Four to Six Maturity Levels.	General: Worker training	No. Accessible instrument and online application is a project goal

(*Continued*)

Table 1. (Continued).

#	Source	Model Type	Method	Conceptual Structure	Human Factor(s)	Instrument?
9	(Lichtblau et al. 2015)	IMPULS model measures the willingness and capacity of companies to implement Industry 4.0	Mixed methodology (literature review, expert workshops and survey data)	Five Aspects: Strategy and Organisation; Smart Factory; Smart Operations; Smart Products; Data-driven Services; Employees. Six Readiness Levels: Outsider; Beginner; Intermediate; Experienced; Expert; Top Performer	Specific: Worker skills; Willingness to learn IT skills; Competent at implementing assistance systems	Yes. Industry 4.0 Online Readiness Check. Validity and reliability not addressed
10	(Samaranayake, Ramanathan, and Laosirihongthong 2017)	Technological readiness model organises and weights factors for Industry 4.0	Small-scale literature review. Factors weighted via Q-Sort and expert analytical process	Six *Ranked* Aspects: Human Technology Skills; Device and Systems Interconnectivity; Big-Data Management; Data Sharing Between and Within Organisations; Internet System Development; Data security	Specific: Technology expertise; Knowledge, skills, abilities and motivations of staff, data scientists, and support staff	No
11	(Schuh et al. 2017)	Industry 4.0 Maturity Index for assessing a company's Industry 4.0 maturity stage and next steps	Expert consultations workshops and case studies. Instrument Validated through applications at companies	Five Aspects: Resources; Information Systems; Organisational Structure; Culture. Five Areas: Development; Production; Logistics; Services; Marketing/Sales. Six Maturity Stages: Computerisation; Connectivity; Visibility; Transparency; Predictive Capacity; Adaptability	Specific: Digital-communication abilities of humans and machines; Worker capacities: Openness to change and social collaboration	Yes. A sample item provided only. Stich, Gudergan, and Zeller (2018) note this instrument has 600 items. Validity and reliability not addressed
12	(Ganzarain and Errasti 2016)	Industry 4.0 Maturity Model	Mixed-methods. Expert interviews, literature review of 72 items and concept-mapping	Nine Aspects: Strategy; Leadership; Customers; Products; Operations; Culture; People; Governance; Technology. Five Maturity Levels: Measured on a 5-point scale.	Specific: Collaboration skills; ICT competences; Employee openness and autonomy; Mobile technology competences	Yes, but not provided. Piloted via two Austrian studies. Validity and reliability not addressed.
13	(Scremin et al. 2018)	Adoption Maturity Model (AMM) assessing the maturity level of Industry 4.0 companies	Literature review, structured interviews of managers, case studies, design of maturity thresholds and indicators, and development of archetype matrix	Eight Aspects: Business Strategy; Technology Strategy; Networking and Integration; Infrastructure; Analytical Skills; Absorptive Capacity; Benefits of Adoption; Impact on Efficiency. Maturity Levels: Assessed by researchers via mixed-methods analysis of interview responses.	General: Human factors addressed as 'absorptive capacity' of an organisation; Availability of employee training and awareness of skill requirements for using systems	Interview guide is published. Framework validated through ten case studies. Further validation is planned.

2.2. Worker-level readiness models

The ten reviewed worker-level models are shown in Table 2. At this level of analysis, most models identify detailed complexes of readiness factors derived from literature reviews, roadmaps, survey data and expert interviews. Several models incorporate a generic competence framework addressing technical, methodological, social and personal abilities (Hecklau et al. 2016). Overall, the proposed factor groupings feature social/collaboration competences (2, 3, 5, 6, 8, 9, 10), technical/ICT knowledge and skills (2, 5, 6, 8, 10) and cognitive flexibility (1, 3, 5, 6, 8, 10). Less prominent groupings include intrapersonal competences (3, 8, 9 and 10) and intercultural skills (8 and 9). Departing from predefined factor structures, three models (4, 5 and 7) theorise worker readiness by envisioning new job types, professional archetypes and situational characteristics tied to work dynamics of Industry 4.0 environments. Only two models (5 and 8) report the availability of measurement instrumentation. Although these instruments appear to be sophisticated expert-assessment tools, information is not provided about validation and reliability testing.

2.3. Patterns, limitations and gaps

On aggregate, the reviewed models present a diversity of conceptual structures and constituent readiness factors. At both the organisational and worker levels of analysis, technological and social/communication skills are most prominent. At the worker level, personal flexibility is also emphasised, but elaborated in several ways (e.g. motivation to learn and openness to change). Methodologically, several proposals are grounded tentatively on ad hoc theorisations or small-scale literature reviews, and few provide a systematic description of the target. Also, two conceptual gaps emerge. Firstly, technology-focused dispositional subfactors (e.g. trust and acceptance/enthusiasm) receive little attention. Secondly, competences addressing readiness for new forms of human-computer interaction precipitated by Industry 4.0 automation and augmentation technologies are mostly absent. Here, researchers may be drawing too heavily from mainstream competence discourses that have not adapted to the novel dynamics of human-machine partnering (Grudin 2017). Finally, the meagre availability of valid and reliable instrumentation at both the organisational and worker-levels of analysis suggests these models are mostly early-stage proposals. Given these findings, an original modelling procedure was initiated to consolidate prior research, address conceptual gaps and establish a theoretical foundation for implementing a worker readiness profiling application.

3. Purpose and method

A two-phase modelling procedure based on an integrative literature analysis and synthesis was conducted. As shown in Figure 1, phase one deployed an activity-system apparatus (Engeström 2015) for deriving a structured description of the target work environment. Activity theory was chosen because it has demonstrated usefulness over many decades for modelling workplace transformations (Virkkunen and Newnham 2013; Engeström 2005) and the socio-technical dynamics of human-computer interaction (Nardi 1996; Kaptelinin and Nardi 2012). Activity theory originated in early Soviet psychology of the 1920s with Vygotsky's (1978) triangular model in which *tools and technologies* were positioned as mediators between *subjects* and their *objects*. This foundational social-psychological structure was elaborated into a system of collective (labour) activity by Leontiev (1977, 2005, 2006) in which *rules, other actors* (e.g. members of a workgroup) and *divisions of labour* were added. Finally, the Finnish scholar Engeström consolidated these elements visually in a (multi-triangle) activity system apparatus, which has been used extensively in several scientific disciplines for abstracting, explaining, positioning and contextualising work activity (Bligh and Flood 2017).

Phase two focused on coding, extracting and organising KSAs into thematic clusters aligned with the target. This phase relied on a multidisciplinary base of social science, human factors and Industry 4.0 literature, which addressed worker/operator competences supporting optimal functioning in digitalised work environments.

For both phases, English-language literature was identified and analysed via an emergent process. An initial set was established by querying Google Scholar and Web of Science using predefined keywords (e.g. [readiness OR skills OR competence] AND [manufacturing OR digitalisation OR Industry 4.0]). As items were reviewed, additional phrases (e.g. cyber-physical systems; Industry 4.0 human factors; Operator 4.0) were gathered to extend the set. Published articles and high-quality conference papers were preferred, but other publication types were included if they provided

Table 2. Worker-level Industry 4.0 readiness models compared.

#	Source	Model Type	Method	Factor Types	Factor Clusters	Instrument?
1	(Adolph, Tisch, and Metternich 2014)	Workforce competences and learning for production efficiencies	Workforce competences derived from production challenges and megatrends via small-scale literature review	Competences	FlexibilityChangeabilityResource efficiencyProcess efficiency	No
2	(Dworschak and Zaiser 2014)	Competences of workers in manufacturing contexts of cyber-physical systems.	Skills drawn from technology forecasts and organisation structures. Tool scenario: humans contribute to decisions; Automation scenario: IT makes decisions	SkillsKnowledge	TechnicalSocial and Collaboration; Deep Operational and Business Informational;IT and Engineering knowledge	No
3	(Erol et al. 2016)	Taxonomy of competences of Industry 4.0 workers and scenario-based learning-factory (TU Wien)	Based on a small-scale literature review of competences for digitalised production, and experience developing a learning factory	Competences	Personal (reflect, act autonomously, learn; trust); Social (communicate, cooperate, use social media); Action (interdisciplinarity, manage parallel structures); Domain (model, analyse)	No
4	(Fareri et al. 2018)	Effects of Industry 4.0 on business value chains, and the competences of worker job profiles	Modified Porter value-chain model to map business functions and select literature. Automated text mining to analyse literature. Matrix created to cross-reference business functions and Industry 4.0 worker profile archetypes	Archetypes	Data Architect (all depts); IT Architect (logistics and IT); Geek (management, facilities); Investigator (facilities, QC); Perfectionist (facilities, QC, accounting); Prophet (IT, production); Strategist (marketing, management, R&D)	No
5	(Galaske et al. 2017)	Toolbox Workforce Management 4.0. Readiness of businesses, workforce competences and work conditions	Small-scale literature review. Theorised using Guideline Industrie 4.0 and Generic Procedure Model for SMEs. Matrix with application fields as vertical elements and development stages as horizontal elements	Skills CompetencesEnvironmental variables	Hard Skills: IT, business and manufacturing;Soft Skills: personal, social and methodical competence Environment: assistance systems, human-machine interaction, decision support, security/privacy, organisational flexibility	Graphical model to guide interviews and assessment.
6	(Gehrke et al. 2015)	Skills and qualificationsfor future manufacturing workers	Industry 4.0 modelled via the experience of 10 engineers. Contextual factors: cooperation, working environment; Organisation and structure; Tools and technologies; Tasks: from physical objects to information, models and simulations	SkillsQualifications (organised by 'Must have', 'Should have' and 'Could have')	Technical: Must have IT, data processing, organisational understanding; Should have knowledge management skills; Could have programming abilities; Personal: Must have adaptability and social skills; Should have trust in technologies and a learning mindset; No could haves	No
7	(Hartmann and Bovenschulte 2013)	Proposal for deriving skill needs for Industry 4.0 from technology roadmaps	Skills derived from road-mapping expert input. Roadmaps address equipment; robotics and automation; human-machine collaboration and bio-engineering	Skills (adaptive to business contexts)Roles	Organisational Scenarios: yield different skill needs; Roles: Industrial ICT Specialist, Industrial Cognitive Scientist, Automation Bionics Specialists	No
8	(Hecklau et al. 2016)	Holistic human resource management for Industry 4.0	Employee competences derived from Industry 4.0 drivers/challenges identified via a literature review. Challenges organised in five categories: political, economic, social, technical, environmental and legal	Competences	Technical: media, coding, security; Methodological: creativity, entrepreneurial thinking, problem-solving; Social: intercultural, communication, teamwork, negotiation; Personal: flexibility, ambiguity tolerance, learning	Radar charts for competence visualisation
9	(Mittelmann 2018)	Competences for Work 4.0, success factors for businesses of the future.	Small-scale literature review. Characteristics of Work 4.0 identified as digitalisation, collaboration with cyber-systems, flexible, work independent of location and time, complex non-routine tasks, and diverse teams	Competences	Intrapersonal: critical thinking, sense-making, adaptive thinking, transdisciplinarity, self-direction; Interpersonal: communication, virtual collaboration, social and intercultural intelligence; ICT: computational thinking, social media, Information security	No
10	(Mourtzis 2018)	Skills and competences for Industry 4.0	Competences derived from literature review of Industry 4.0 technology descriptions. Proposal for Education 4.0 based on teaching factories	Knowledge Skills	Technical: technological, learning, process understanding; Methodological: creativity, problem-solving, analytical, research; Social: communication, cooperation, networking; Personal: autonomy, responsibility, organisational, flexibility	No

original perspectives and evidence-based analyses of Industry 4.0 work environments or worker competences. Literature was admitted from several academic domains and national contexts without prejudice. (Within the coded literature, 35% of the first authors reported Germany or Sweden as their host nation, with 36 nations represented.) Host journal domains included engineering, business, information technology, computer science, psychology, ergonomics and education. Most items dated from 2015 (115). Searching stopped when the thematic extraction/coding of activity-system characteristics and worker competences (in Excel) reached saturation (Mason 2010). The final (135-item) data set (maintained in Endnote X9) included 63 articles, 44 conference papers, 12 chapters and 16 reports. A semantic analysis of abstracts and keywords (conducted in NVivo 12) highlighted both context-specific (e.g. Industry, manufacturing, technology, systems and digitising) and worker-related items (e.g. humans, work, skills and competence) among the top 100 lexemes, which is consistent with the study's twin focus. *To achieve economy in reporting, references provided in this text are selective and do not represent the full data set.*

4. Stage 1 findings: target work environment

A structured multidimensional description of Industry 4.0 work environments was achieved by addressing each of the six activity-system elements (shown in Figure 1). This approach resulted in a generic target model, and it is expected that the characteristics of any particular industrial workplace will be shaped by national context, industrial sector, management culture and level of technological maturity (Da Silva et al. 2019).

4.1. Object(s)

The object of an activity system incorporates motivating objectives and desired outcomes. A principal object of Industry 4.0 is rooted in its conception. Industry 4.0 was announced as a strategic initiative to bolster the German manufacturing sector and national economy (Xu, Xu, and Li 2018). Other nations followed with similar digitalisation initiatives to maintain global competitiveness. For example, South Korea introduced 'manufacturing innovation 3.0', and Japan launched 'Society 5.0' (Oztemel and Gursev 2018). Beyond strengthening economies, Industry 4.0 is also widely regarded as a pathway towards greater environmental sustainability (Chen, Olhager, and Tang 2014; Jackson 2016; Sutherland et al. 2016) and social innovation (Morrar, Arman, and Mousa 2017), which function as secondary objects. A third object emphasises technological innovation as a pathway to a new industrial age (Zhong et al. 2017). Of course, objects are always shaped by, and formulated within, organisational and cultural contexts of activity.

4.2. The worker

As a system entity, the literature positions Industry 4.0 workers as adaptable, 'informationalised' and hybridised. Technologically complex production environments supporting customised products in small batch sizes (Järvenpää, Lanz, and Lammervo 2016) requires

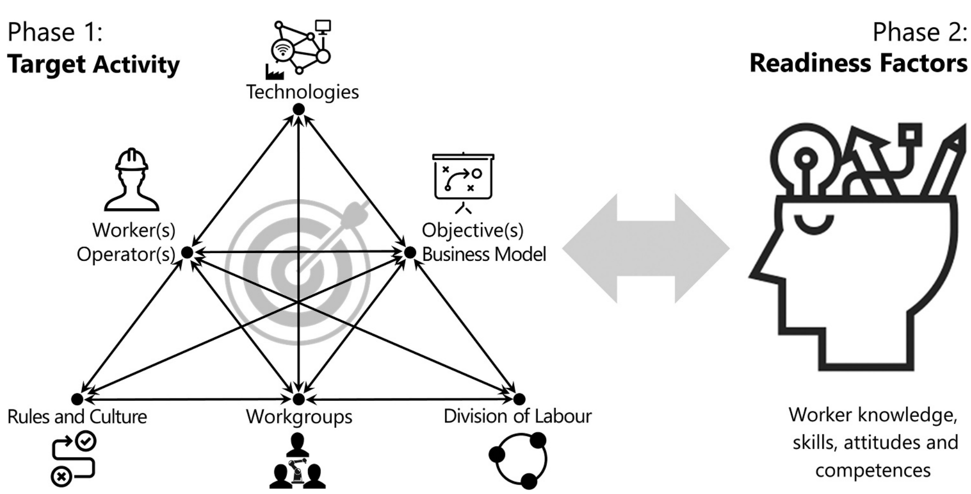

Figure 1. Two-phase deductive literature analysis and modelling approach.

workers who are *adaptable* to reconfiguration and emergent problems. The *informationalised worker* calls attention to humans as data producers and processors. As producers, workers routinely input data (e.g. task logging) or generate physiological and environmental information with wearable sensors. As information processors, they are required to generate actionable intelligence from multiple data streams (Dworschak and Zaiser 2014). The *hybridised worker* emerges through advanced (e.g. brain-computer) interfaces and augmentation systems (Zhong et al. 2017; Mourtzis 2018). For example, SOPHOS-MS incorporates VR and natural-language-processing, enabling operators to receive expert knowledge on-demand through a question-and-answer approach (Longo, Nicoletti, and Padovano 2017). Similarly, the Operator 4.0 paradigm envisions the dynamic augmentation of a worker's physical, sensorial and cognitive capacities (Romero et al. 2016a; Peruzzini, Grandi, and Pellicciari 2020; Romero et al. 2016b) to serve several manufacturing functions (Ruppert et al. 2018). Other hybridisation models, such as intelligent-adaptive assistance, have also been proposed (Wilkesmann and Wilkesmann 2018).

4.3. Technologies

Companies striving toward Industry 4.0 seek to exploit the full capabilities of cyber-physical systems (Choi et al. 2017). Lists of enabling technologies feature the Internet of Things, cybersecurity, big-data analytics, cloud computing, additive manufacturing, augmented reality and advanced interfaces (Rüßmann et al. 2015; Geissbauer, Vedso, and Schrauf 2015). Going beyond lists, some researchers have developed holistic frameworks. For example, Frank, Dalenogare, and Ayala (2019) distinguish between 'front-end technologies,' supporting operational and market needs, and 'base technologies,' providing connectivity and intelligence. Base technologies include IoT, Cloud computing and big data, enabling advanced applications like digital modelling ('twinning') of machines and factory environments to automate decision making and anticipate maintenance requirements. Front-end technologies include four 'smart' technological clusters related to manufacturing, products, supply chain and working. From a greater level of abstraction, Qin, Liu, and Grosvenor (2016) reduce Industry 4.0 technologies to *interoperability* and *consciousness*. Interoperability includes technologies of communication, flexibility, real-time responsibility and customizability. Consciousness emerges through those technologies facilitating predictive intelligence, decision making, self-awareness, self-optimisation and self-configuration.

4.4. Workgroups

Workgroup configurations in Industry 4.0 are described as hybridised, diverse, geographically distributed and dynamic (Mittelmann 2018). Patterns of interaction, ranging from coexistence to collaboration, and incorporating human and machine entities (often situated in different physical locations), will be deployed strategically and contextually to address emergent operational opportunities and challenges (Galaske et al. 2017). Workgroups are expected to favour network structures that flatten hierarchy and promote interaction across traditional departmental boundaries (Schuh et al. 2014). Owing to the twin dynamics of vertical and horizontal systems integration, communication requirements within and between workgroups will intensify (Schuh et al. 2014). Within these well-connected network structures, managers and other human authorities will increasingly share decision-making control with non-human actants (Fischer and Pöhler 2018).

4.5. Rules and culture

Worker autonomy and decentralised decision-making are leading themes in this category (Fischer and Pöhler 2018; Karacay 2018; Galaske et al. 2017). Production environments will achieve optimal performance where front-line operators, supported by expert systems, have the resources to address problems directly (Järvenpää, Lanz, and Lammervo 2016; Shamim et al. 2016). Realising the advantages of distributed problem solving, however, can be challenging in contexts where centralised control, associated with scale economics, is well established (Frank, Dalenogare, and Ayala 2019). Two less emphasised themes address service- and technology-oriented subcultures (Herterich, Uebernickel, and Brenner 2015; Soulé and Warrick 2015). A service-oriented subculture is vital to supporting data-driven offerings requiring close relationships with customers throughout a product's lifespan (Ibarra, Ganzarain, and Igartua 2018). A technology-oriented subculture promotes enthusiasm for learning new systems, applications and interfaces (Richter et al.

2017). Some case studies demonstrate that technology enthusiasm can be cultivated effectively 'from below.' For example, Johansson (2017) observed a young machine worker with computer gaming experience successfully mentoring mature operators (with tremendous domain knowledge) as they struggled to use new front-line, computer systems.

4.6. Division of labour

To address the impact of digitalisation on divisions of labour, researchers have shifted focus from studying job roles to *tasks* (Nokelainen, Nevalainen, and Niemi 2018). The dated model of Autor, Levy, and Murnane (2003) analysed tasks along two axes (manual/cognitive and routine/non-routine), positing that both manual and cognitive *routine* tasks, which follow explicit rules, are susceptible to automation. Frey and Osborne (2017) recognised that advances in AI and machine learning have significantly increased the automation of *non-routine* tasks. However, they argued that humans remain advantaged in three categories: (a) perception and manipulation, (b) creative intelligence, and (c) social intelligence. Similarly, Koorn, Leopold, and Leopold (2018) organised work tasks into eight types and found that creative and adaptive tasks were the most difficult to automate. Difficult or not, generative AI models like GPT-3 continue to extend the creative capacities and potential roles of non-human agents (OpenAI 2020; Elkins and Chun 2020).

Other researchers have explored emerging divisions of labour through the lenses of dynamic augmentation and human-robot cooperation (Peruzzini, Grandi, and Pellicciari 2020). Romero et al. (2016a), for example, design systems that respond dynamically to deficits in human physical, sensorial and cognitive performance, and Richert (2018) describes hybrid forms of collaboration in a virtual factory. In general, Industry 4.0 research highlights a shift from the design-time allocation of human tasks to *run-time* and *mixed-agent* task distributions.

4.7. Summary of target activity characteristics

Based on the research synthesis presented above, Table 3 summarises the activity-system characteristics of Industry 4.0. The next section identifies and organises worker-level readiness factors aligned with this target.

Table 3. Key characteristics of Industry 4.0 modelled as an activity system.

#	System Element	Key Characteristics
1	Object(s)	Productivity and global competitiveness Sustainability and social innovation Technological innovation
2	Worker	Adaptive entity, responsive to dynamic work environments Driven, maintained and defined by data Hybridized or machine augmented
3	Technologies	Enabling technologies: Internet of Things, Cloud, AR/VR, big data, additive manufacturing, cybersecurity, robotics, advanced interfaces, etc. Holistic typology: Technologies of smart manufacturing, smart products, smart supply chain and smart working Core purposes: interoperability and consciousness
4	Workgroups	Hybridised, featuring new agentic entities and roles Culturally diverse and geographically dispersed Emergent teams, roles and goals
5	Rules and Culture	Increasing levels of autonomy Decentralised decision-making Service-oriented, customer-relationship culture Culture of techno enthusiasm
6	Division of Labour	Increasing automation of non-routine and complex tasks Human workforce more focused on creative strengths Tasks taken up dynamically based on situational needs and an agent's/operator's (measured) level of performance

5. Stage 2 findings: dimensions of worker readiness

Worker competences, incorporating KSAs aligned with the target, were extracted from the literature and organised into five dimensions. Three dimensions (technological, flexibility and interpersonal readiness) consolidate and extend complexes addressed by other models. Inter-agent and innovation readiness are original proposals synthesising KSAs represented strongly in Industry 4.0 literature but not yet prominent in most worker readiness models.

5.1. Technological readiness

This dimension aggregates three abilities complexes. The first represents *foundational digital skills*. Typically developed through regular use of mainstream hardware (e.g. personal computers and mobile devices) and software/apps, these skills offer an essential starting point for digitalised work (Canadian Apprenticeship Forum 2018; Johansson 2017). Digital-competence researchers have produced validated instruments to measure these skills across several categories of use (van Deursen, Helsper, and Eynon 2016; Blayone et al. 2018a). The Industry 4.0 literature, however, places greater emphasis on *advanced technology/IT competences* often requiring formal learning and on-the-job training (Fonseca 2018; Foresti and Varvakis 2018; Ghobakhloo 2018; Muro et al. 2017). This complex includes KSAs supporting networking and information processing, data analysis, and working with raw materials, smart objects, automated guided vehicles (AGVs) and complex software interfaces (Schallock et al. 2018; Erol et al. 2016). A third complex, addressing *attitudinal dispositions* toward information technology also achieve prominence. For example, Oesterreich and Teuteberg (2016) and Johansson (2017) highlight technology acceptance and low technology anxiety as orientations promoting effective human-machine interaction. Interest in learning about IT (Gokhale, Brauchle, and Machina 2013), self-direction (Raemdonck, Thijssen, and de Greef 2017) and personal initiative (Frese and Fay 2001) are all intrapersonal factors supporting IT-skills development. One caveat regarding skill acquisition is that emerging augmentation systems are expected to provide unskilled operators with situationally relevant expert procedures as required (Longo, Nicoletti, and Padovano 2017). Therefore, it appears that some operator jobs will require well-aligned attitudes and general digital skills rather than specialist knowledge of materials and procedures.

5.2. Interpersonal readiness

Research in affective computing (Wu, Huang, and Hwang 2016) and social robots (Belpaeme et al. 2018) describe systems that capture, reproduce and even 'feel' emotion. Nevertheless, a capacity to respond situationally to the states and behaviours of humans remains a challenge for machines and is considered distinctly human strength (Frey and Osborne 2017). Thus, workers do well to cultivate networking competences (Erol et al. 2016) and social and negotiation skills (Bhattacharyya 2018). Others highlight cross-cultural and online-communication competences for working effectively within geographically dispersed teams (Hämäläinen, Lanz, and Koskinen 2018; Holtkamp, Lau, and Pawlowski 2015).

Despite the prominence of interpersonal skills among Industry 4.0, 21st-century skills and digital-competence readiness frameworks, manufacturers are advised to consider worker competence priorities against their operational goals. To address this point, Weber, Butschan, and Heidenreich (2017) investigated the effects of cognitive, social and processual competences on technological maturity and performance outcomes at German factories by surveying 284 employees in production and innovation departments. A key finding was that, unlike cognitive and processual competences, social competences showed no positive relationship to levels of technological maturity. This finding suggests a situational exception to the general importance of interpersonal competences. Namely, that those organisations focused on technological transformation should give the development of cognitive and processual competences of mission-critical workers the highest priority.

5.3. Flexibility readiness

Flexibility readiness incorporates three sub-groupings incorporating (a) *multidisciplinary* knowledge (Freddi 2018; Ghobakhloo 2018), (b) *openness* to dynamic roles and emergent problems (Erol et al. 2016), and (c) *comfort* with technological change (Fischer and Pöhler 2018; Schallock et al. 2018). In each case, levels of human adaptability will be shaped by cultural and personal dispositions. For example, tolerance of ambiguity is a well-studied value orientation in the field of cross-cultural analysis (Hofstede 2001), and openness to new experiences is a 'Big 5' personality trait (Azucar, Marengo, and Settanni 2018). Thus, Nokelainen, Nevalainen, and Niemi (2018) argue that workers may often carry a predisposition towards stability (an 'entity mindset') or openness to change (an 'incremental mindset'). Nevertheless, some empirical studies find that cognitive flexibility and environmental adaptiveness are increased through education and training (Hytönen et al. 2016). From this orientation, learning factories have been designed to augment classroom learning and simulate the dynamic working conditions of digitalised industrial environments (Schallock et al. 2018).

5.4. Inter-agent readiness

This dimension focuses on interactions between different types of *agents* inclusive of human, non-human and hybrid entities (Gladden 2019). An agent is an autonomous entity with the capacity to act towards its goals and interact with other agents when it cannot reach its objectives alone (Leitão 2009). An *intelligent* agent must be able to mobilise resources, reflect on actions and adapt to changing circumstances (Romero et al. 2016a).

Within cyber-physical systems of Industry 4.0, human, system and robotic entities will achieve intelligent agency, at least when functioning optimally. Human workers must prepare to achieve optimal levels of comfort and performance within tightly integrated human-machine assemblages – a challenge greatly influenced by the design of human-machine interfaces (Peruzzini, Grandi, and Pellicciari 2020).

Readiness factors enabling optimal inter-agent functioning include numerous KSAs, with attitudes achieving as much prominence as knowledge and skills. Two critical *attitudes* are openness to human-machine partnering (Becker and Stern 2016) and trust toward technological entities (Hoff and Bashir 2015), including robots (Richert 2018), decision-automation systems (Lee and See 2004), big-data analytics (Akdil, Ustundag, and Cevikcan 2018) and augmentation apparatuses (Mourtzis 2018). Pacaux-Lemoine et al. (2017) find that a worker's willingness to trust a machine agent is inversely related to their level of self-confidence, highlighting a vital intrapersonal nuance for measuring readiness. In short, self-confidence is a double-edged sword. Rajaonah et al. (2008) extend this scheme with three mediating variables: perceived workload, perceived risk, and perceptions of system effectiveness.

In this dimension, essential knowledge and skills include the ability to (a) model the functioning of non-human agents; (b) communicate in ways that non-human agents can readily process; and (c) calibrate levels of dispositional trust by assessing the situation, performance histories and potential consequences (Pacaux-Lemoine et al. 2017). Pacaux-Lemoine et al. (2017) designed a manufacturing scenario to explore the performance dynamics of human-machine partnering. The experimental design dictated that throughput and energy use were to be balanced in a production environment where some machines malfunctioned and moving products to different machines increased energy use. The three control conditions tested were automation, human control, and human-machine cooperation. Human-machine cooperation achieved the best performance, but the inter-agent skills of the human operator emerged as a significant mediating variable.

More generally, within the research, human-machine partnering and co-agency are challenging traditional human-tool interaction perspectives (Grudin 2017). Jones, Romero, and Wuest (2018) explain that the well-established concept of *interacting with* machines addresses two general system configurations. On the one hand, tasks may be performed by a human operator monitoring and controlling a machine. On the other hand, a machine may perform all activities under normal circumstances with a human taking over when a problem has been identified. In both bases, a *physical* human-machine interface is available to be mastered by the operator. The move towards co-agency between humans and machines shifts focus to *cognitive* interfaces that introduce new requirements for communication and collaboration between agents. Of course, identifying these requirements remains an essential work in progress because such interfaces are still being designed in research labs.

5.5. Innovation readiness

Frey and Osborne (2017) identified innovative thinking and creative intelligence as an incredibly difficult area for machine-automation. Although AIs are generating impressive forms of visual art, music and creative writing (McCormack, Gifford, and Hutchings 2019; Sturm et al. 2018), it remains challenging to automate problem-solving in dynamic environments where solutions must achieve situational effectiveness (Nokelainen, Nevalainen, and Niemi 2018). Therefore, human workers tend to be the most capable entities for generating (useful) novel ideas, refining and evaluating these ideas, functioning collaboratively and learning from failures (Soulé and Warrick 2015).

Nevertheless, given the increasing need to ground innovative solutions on big-data analyses and simulations (Vaidyaa, Ambadb, and Bhosle 2018), creative problem-solving is expected to evolve as a hybrid process incorporating humans and automation systems (Carlsson 2018). To what extent intelligent machine agents will ultimately direct human operations ('automation scenario') or merely suggest courses of action ('tool scenario') in any given context remains an open question (Dworschak and Zaiser 2014). Indeed, there are still several systems-integration challenges hindering the effective coordination of multiple actors in strategic processes (Sanchez, Exposito, and Aguilar 2020). In the end, owing to the ongoing need for humans to generate or support creative data-driven solutions to emergent operational problems, innovation readiness is proposed as a fifth dimension.

5.6. Summary of proposed worker readiness dimensions

Table 4 summarises, and Figure 2 visualises, the resulting five-dimensional model of worker readiness for Industry 4.0. Although technological, interpersonal and flexibility readiness are addressed by previous research, this model calls attention to additional sub-factors. The inter-agent and innovation dimensions are new proposals featuring KSAs with high prominence in the sampled literature. Contextual considerations are suggested to emphasise that optimal factor structures must be adapted to local needs/cultures.

6. Discussion

This study produced a new model of worker readiness for Industry 4.0 via a two-stage research synthesis addressing research gaps in 23 prior models. In stage one, it deployed an activity-system apparatus to generate a structured description of the target work environment addressing six elements: the worker/operator, technological systems, guiding objectives, organisational culture and divisions of labour. This approach improved upon many previous ad hoc descriptions. In stage two, this study identified and organised five dimensions of worker readiness strongly aligned with the target. Like 21st-century and digital-skill frameworks

Table 4. Proposed five-dimensional model of worker readiness for Industry 4.0.

#	Readiness Factor	Readiness Subfactors (KSAs)	Contextual Considerations
1	Technological	(1) Foundational digital skills (2) Advanced IT skills (3) Attitudinal orientations and intrapersonal skills supporting enthusiastic IT use skill development	Level of Industry 4.0 technological maturity Presence of adaptive augmentation systems towards Operator 4.0
2	Flexibility	(1) Multidisciplinary knowledge (2) Openness to dynamically assigned roles and tasks (3) Tolerance of environmental dynamism and emergent problems	Stubbornness of traditional (hierarchical) organisational cultures Broader socioeconomic pressures on manufacturing operations Level of Industry 4.0 technological maturity
3	Inter-agent	(1) Attitudes of openness and comfort toward human-machine partnering (2) A well-calibrated level of trust toward technological agents and automation systems (3) Knowledge and skills for modelling, communicating and calibrating trust with machine agents/robots	Availability and sophistication of collaborative robots, adaptive augmentation systems, wearable tech, expert systems and machine agents Organisational decision-making protocols
4	Interpersonal	(1) Social-networking competencies (2) Communication and negotiation skills (3) Attitudes and skills supporting digital-mediated collaboration problem-solving in dispersed, cross-cultural teams	Distribution of responsibilities among agents in cyber-physical systems Location and diversity of teams Levels of interaction, ranging from coexistence to collaboration, required to achieve objectives
5	Innovation	(1) Creative and adaptive strategic-thinking skills (2) Data-analysis knowledge and software application skills	Creative capabilities of humans and other agents Organisational culture/rules related to conservatism and innovation Level of Industry 4.0 technological maturity

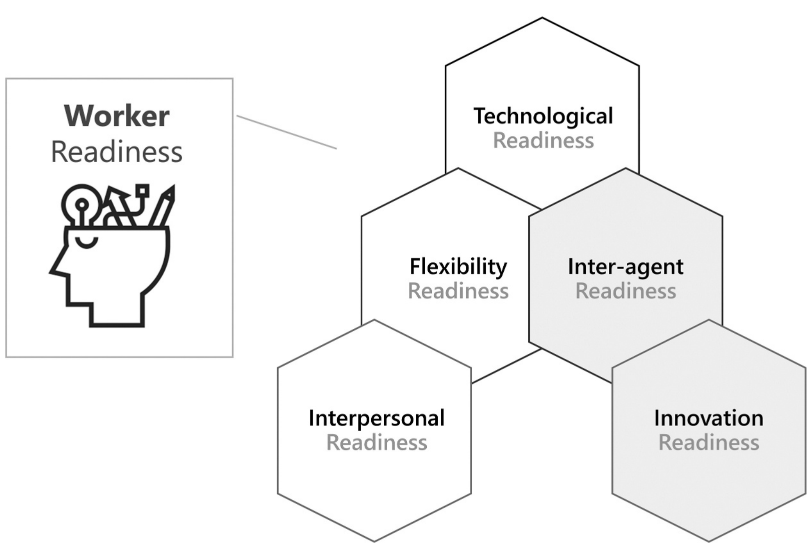

Figure 2. Visual presentation of the proposed five-dimensional worker readiness model, with the two original dimensions highlighted.

(van Laar et al. 2017), the proposed model acknowledged the importance of technical, social and flexibility-related KSAs also featured in other Industry 4.0 models. However, it extended these dimensions, emphasising *advanced* technological skills and mediating attitudes, such as trust in technology. More importantly, it introduced two original dimensions (comprised of inter-agent and innovation competences) vital to successful human-machine partnering and creative problem-solving in dynamic Industry 4.0 environments. Noteworthy empirical investigations of human-robot collaboration (Richert 2018), trust in automation systems (Hoff and Bashir 2015) and operator-augmentation architectures (Longo, Nicoletti, and Padovano 2017) were selected to highlight emerging operating scenarios characteristic of Industry 4.0 overlooked by mainstream digital-competence frameworks (Eshet 2012; Ferrari 2013; Desjardins, Lacasse, and Belair 2001; van Deursen, Helsper, and Eynon 2016).

The authors' next steps are to (a) theorise the constituent competences of inter-agent and innovation readiness more fully, (b) triangulate the model via case studies and observational data, and (c) proceed towards operationalisation and the launch of an online readiness profiling application based on the Global Readiness Explorer (GREx) platform developed by the EILAB (vanOostveen et al. 2019). Existing survey tools or selected subscales may be repurposed to measure technological, interpersonal and flexibility readiness, but a review of available validated instruments must be undertaken. The development of original scales will likely be required to measure inter-agent and innovation readiness. Moreover, industry partnerships will be sought to gather relevant case studies and performance data for model triangulation. This endeavour builds on the authors' prior experience of digitally recording and analysing interactions with mobile devices to validate a digital-competence instrument (Blayone et al. 2018b).

A new readiness measurement application explicitly designed to measure, visualise and compare worker readiness for Industry 4.0 will bring benefits to students, workers, researchers, educators, organisational trainers, human resource professionals, and policymakers. Individual students and workers will have the opportunity to generate a personal readiness profile and compare their results to a target or group profile. Researchers will gain access to an aggregate database with which to perform comparative research or relate self-report measures to performance data. Educators and trainers can use relevant group profiles to help identify readiness gaps and adapt educational experiences (technologies, learning methods and content) to address them. Human resource professionals and policymakers will gain access to empirical data with which to align competency-development targets and training interventions with workers' preparation needs. Readiness profile data and accompanying research might also help technologists and engineers design more robust human-machine interfaces and worker-augmentation systems. All of this contributes to a more prepared workforce and more robust industrial systems.

Three limitations of this study are acknowledged. Firstly, the selection of Industry 4.0 as a defining construct skewed the focus towards a German and European perspective. However, the authors recognise Industry 4.0 to be a dominant innovation program (Xu, Xu, and Li 2018; Wang 2018), and the proposed readiness model to be adaptable to digitalised manufacturing more broadly conceived. Secondly, Industry 4.0 remains a rapidly evolving construct. The dynamics of inter-agent readiness may be especially sensitive to change as several research fields (e.g. machine learning, collaborative robotics and dynamic augmentation systems) are actively redefining human-machine interaction. Finally, the proposed model represents a *first-stage* conceptual contribution to a fully operationalised Industry 4.0 readiness framework and worker profile application. The dimensions of inter-agent and innovation readiness, as new proposals, require further conceptual specification incorporating findings from the most current empirical studies.

6.1. Conclusion

This study was initiated by a broader research-and-development program aimed at implementing an Industry 4.0 readiness profile application to collect individual-level data around the globe. Achieving a well-structured conceptual model of worker readiness for Industry 4.0 grounded on a significant literature base is a necessary first step towards this goal. Owing to the dependence of digital and 21st-century skills frameworks on mainstream human-computer interaction models (Grudin 2017) and conceptual gaps in Industry 4.0 readiness models, a more comprehensive model was developed through a two-phase research synthesis. This five-dimensional model consolidates three dimensions featured in prior research. It also introduces inter-agent and innovation readiness as new proposals addressing human-machine partnering and dynamic problem-solving within digitalised workplaces. As noted, the next steps for participating researchers are to (a) review the availability of existing instrumentation for measuring worker readiness in each dimension, (b) generate case-study and observational data to triangulate the conceptual proposal, and (c) select or develop scales for generating reliable and valid profiles of worker readiness for Industry 4.0.

In the end, this study presents an original and reasonably comprehensive foundation on which to develop new tools that enable researchers, educators, trainers, human resource managers, policymakers and system designers to equip workers with the competences and technological affordances for success in Industry 4.

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Dedication

We dedicate this study to the workers of General Motors automotive plants in Oshawa, Canada who, in the face of plant closures, are conquering the challenge of learning new skills as manufacturing transitions towards Industry 4.0.

Disclosure statement

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