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Behavioral training of engineering professionals and students for Industry 4.0

Capacitação comportamental de profissionais e estudantes de engenharia para a Indústria 4.0

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Abstract

Purpose: To present suggestions for behavioral competency development for engineers and Engineering students to work in Industry 4.0.

Originality/value: A human-machine collaboration model (with artificial intelligence application) is proposed for training engineering professionals for the workplace. The behavioral skills for Industry 4.0 to be developed in Engineering degree programs and the quality of evidence of their inclusion in such programs of the Federal University of Rio de Janeiro (Universidade Federal do Rio de Janeiro [UFRJ]) are assessed.

Design/methodology/approach: The engineer-machine collaboration model draws on Design Thinking (Brown, 2010) and cognitive modeling of engineers based on a model of logical reasoning (Paul & Elder, 2002), integrating the cognitive model with a model of information flows in human-machine interactions (Riley, 1989). A competency model for Industry 4.0 (Prifti et al., 2017), interviews with leaders of Engineering schools of UFRJ, addressing their planning for the implementation of the new National Curriculum Guidelines for Engineering programs (Resolução no. 2, 2019), and application of the GRADE approach (Balshem et al., 2011) supported the identification of evidence of behavioral competencies for Industry 4.0 in the undergraduate programs.

Findings: Engineering professionals train their critical analysis and decision-making skills while the machine searches for and processes information and performs simulations. Low quality evidence was found for the training of undergraduates in emotional intelligence, decision-making, and customer relations. No evidence was identified of training in self-management, entrepreneurship, and understanding of the business model.

Keywords: engineers training, engineer-machine collaboration, behavioral competencies, Industry 4.0, AI

Resumo

Objetivo: Apresentar meios de capacitação comportamental de profissionais e estudantes de engenharia para Indústria 4.0.

Originalidade/valor: Este estudo propõe um modelo de colaboração homem-máquina inteligente (aplicação de IA) para capacitação de profissionais de engenharia no local de trabalho. Identifica e qualifica evidências de competências comportamentais para Indústria 4.0 a serem desenvolvidas nos cursos de graduação em Engenharia da UFRJ.

Design/metodologia/abordagem: O modelo de colaboração engenheiro-máquina abrange o *Design Thinking* (Brown, 2010). Trata-se de uma modelagem cognitiva do engenheiro adaptada ao modelo para o raciocínio lógico (Paul & Elder, 2002), com a integração da modelagem cognitiva ajustada ao modelo de fluxo de informações de interação homem-máquina (Riley, 1989). A implementação do modelo de competência para Indústria 4.0 (Prifti et al., 2017), a entrevista com dirigentes da EQ e Poli (UFRJ) sobre o planejamento para implementação das novas DCN de Engenharia (Resolução nº 2, 2019) e a aplicação da abordagem GRADE (Balshem et al., 2011) para qualificação do nível de confiança suportaram a identificação de evidências de competências comportamentais para Indústria 4.0 na graduação.

Resultados: Os profissionais de engenharia treinam análise crítica e tomada de decisão, enquanto a máquina busca/processa informação e realiza simulações. Os cursos de graduação da EQ/Poli da UFRJ apresentam baixa evidência quanto à qualificação dos alunos em “inteligência emocional, tomada de decisão e relação com cliente”. Não foram identificadas evidências quanto à capacitação dos estudantes em “autogestão, empreendedorismo e conhecimento de modelo de negócios”.

Palavras-chave: capacitação de engenheiros, colaboração engenheiro-máquina, competência comportamental, Indústria 4.0, IA

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INTRODUCTION

Industry 4.0 encompasses advances in the areas of automation, sensors, artificial intelligence, and information and communication technologies based on hyperconnectivity and high degrees of digitalization and senses, making the world increasingly interconnected and interdependent (Hermann et al., 2016). The emergence of a new human-machine relationship (Farooq & Grudin, 2016), based on collaborations between humans and artificial intelligence (AI), has the potential to reshape the way engineers work in the future, calling for a reformulation of engineering *curricula* to account for the need for graduates to acquire specific behavioral skills, as well as technical skills.

One notable development for the workplace in terms of human-machine collaboration is APPsist. Developed by scientists from the Fraunhofer Institute and implemented at the German multinational Festo, it is a mobile device embedded with an intelligent assistant system that supports the training of production professionals for Industry 4.0, with instructions for process optimization and troubleshooting (Ullrich et al., 2016).

Prifti et al. (2017) developed a competency model for Industry 4.0 for Information Systems, Computer Science, and Engineering students at the University of Munich. The model presents a list of competencies that students from these three programs need to master to be able to work successfully in Industry 4.0.

One of the biggest challenges associated with the emergence of Industry 4.0 is how to ensure engineering professionals are trained to work in the workplace reconfigured by this new paradigm (Marra et al., 2017). The training should begin at the undergraduate level, preparing students with the necessary competencies. As such, this article addresses the following research question:

- How can Engineering professionals and students be trained to operate in Industry 4.0?

In the engineer-AI collaboration model, the engineer employs critical analysis and decision-making skills, while the machine seeks and processes information and performs simulations for concrete product development situations, focusing on new materials. The two agents (engineer and AI) communicate through intelligent interfaces – voice, gesture, facial expression, body language recognition, and eye tracking – depending on the context. The undergraduate programs of the School of Chemistry and the Poly-

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technic School of the Federal University of Rio de Janeiro (Universidade Federal do Rio de Janeiro [UFRJ]) were found to present low-quality of evidence regarding the training of students in "emotional intelligence, decision-making, and customer relations". No evidence was identified regarding their training in "self-management, entrepreneurship, or understanding of the business model".

This study contributes to the literature by providing a starting point for more in-depth discussions and debates on the training of engineers for smart work environments in the context of the exponential growth of unstructured data. It is expected that this article helps raise educators' awareness as to the importance of designing *curricula* aimed at the development of behavioral skills for Industry 4.0 so that engineering students can successfully transition from the classroom to the workplace with the ability to perform more strategic functions.

The article is divided into four sections in addition to this introductory section: literature review, methodology, results and discussion, and concluding remarks.

LITERATURE REVIEW

Industry 4.0

Industry 4.0, from the German *Industrie 4.0*, refers to manufacturing settings in which communication technologies provide an interface between the physical and digital worlds, integrating machines, humans, and products. Among the technologies that enable Industry 4.0, there are cyber-physical systems (CPS), the internet of things (IoT), human-machine interaction, big data, and data security (Hermann et al., 2016; Brühl, 2015).

CPS have a physical component – the object perceived by the human senses – and a component related to the virtual (cyber) representation of the physical object (Roth, 2016). Decisions are based on the assessment of information from internal sensors and other cybernetic systems. CPSs control physical processes and use feedback to adapt to new conditions in real time (Sabella, 2018).

The "things" interconnected on the IoT, named smart products, are capable of communicating and exchanging information among each other and with the environment without human interaction, creating the basis for autonomous systems, which play an important role in Industry 4.0 (Roth, 2016).

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Human-machine interaction occurs through smartphones and other mobile devices that have virtual-reality (VR) and augmented-reality (AR) technologies as interfaces. Immersed in VR, users cannot see the real world around them, while AR allows them to see virtual objects overlaid in the real world.

Big data is the term used to refer to the exponential amount of unstructured data that can be captured via interconnected objects, stored, and analyzed. With exponential data creation, confidentiality and integrity are essential, as well as protection against cyberattacks (Zhuang et al., 2017).

Artificial intelligence

The field of AI seeks to understand agents capable of acting autonomously, such as chatbots, which use AI applications to enable longer, unstructured "conversations" with humans (Dale, 2016). The main AI techniques are machine learning, deep learning, computer vision, and natural language processing (Wang & Siau, 2019).

Machine learning (ML) algorithm improves AI performance over time after an initial period of training with large quantities of data without being explicitly programmed (Ertel, 2017). Deep learning is a type of machine learning based on layers of artificial neural networks. Just as *stimuli* are needed for biological organisms to learn, neural networks also need *stimuli*, which are provided by training data containing examples of input-output pairs of the function to be learned (Aggarwal, 2018).

Computer vision is used in industrial applications for optical character recognition (OCR), X-ray vision, to inspect parts for quality assurance purposes, three-dimensional (3D) modeling from aerial photographs, fingerprint recognition, and biometrics (Stone et al., 2016).

Natural language processing is used in applications and services in which the ability to understand human language is key. Jurafsky and Martin (2020) point out two classes of algorithm agents that interact by voice/text/dialogue: agents that use conversations with humans to support them in the execution of tasks and dialogue agents that are digital assistants, such as Apple's Siri and Amazon's Alexa, which give instructions, control devices, and make phone calls.

The adoption and application of AI introduce challenges to business decision-making because, with deep learning, there is no way of knowing how the model reached a particular decision. This has led to the idea of "responsible" AI and, thus, to the concept of explainable AI (Miller, 2019),

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i.e., AI whose outputs are understandable by human experts. This stands in contrast with the "black box" of ML, resulting in situations in which no explanation can be given for why an AI system made a particular decision (Edwards & Veale, 2017).

Human-machine collaboration

Human-machine interaction first came about with the popularization of personal computers and investments in the research and development of systems to be used by people with no specialized knowledge on information technology (IT). The interface is the part of the system people manipulate to trigger actions and receive outputs, which they then interpret to decide what steps to take next.

Intelligent interfaces incorporate resources associated with humans, such as perceiving, interpreting, learning, using language, reasoning, planning, and decision-making. They enhance the efficiency of human-machine communication through voice, gesture, image, face recognition, and eye tracking. In this way, they allow users to interact and engage in a collaborative environment where they communicate, control events and perform goal-oriented tasks (Sonntag, 2015).

Two key technologies that use intelligent interfaces are AR and VR. AR glasses enable users to overlay virtual elements on the real environment, while VR glasses immerse them in an artificial 3D world. Interactive machines draw on real-time data obtained through cameras, microphones, and sensors, as well as information generated via radar, laser, and ultrasound, to extract information and adapt their behavior to users and the environment.

By interacting with the environment and users, intelligent machines can learn and evolve by processing images, language data, or sensors autonomously, linking them to existing knowledge. This evolutionary ability could become an everyday feature of real-world machines and software agents in the digital space (Acatech, 2016; Bahceci, 2016).

The Acatech (2016) study, entitled *Innovation potential of human-machine interaction*, reveals a positive scenario for the future of human-machine collaboration, driven by technological advances in the fields of sensors, actuators, data processing/transmission, and AI.

One concept associated with Industry 4.0 is the augmented operator (Weyer et al., 2015), in which humans' capacity to perceive and act in the physical world is magnified by the possibility of being immersed in VR. CPS

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are transforming the way humans interact with smart systems, just as the internet has transformed the way people interact with information. As digital technologies expand humans' working capacity toward a more strategic focus, the nature of work changes (Sabella, 2018).

The era of human-machine interaction marked by stimulus-response is giving way to collaboration, in which humans and AI are partners in the execution of tasks (Farooq & Grudin, 2016). Stone et al. (2016) highlight AI research efforts aimed at building intelligent systems in which humans are the protagonists. Design Thinking is a powerful methodology used to design, select options, prototype, test, and validate solutions. It combines human needs and technological feasibility to develop innovative solutions in associative reasoning sessions in an iterative process (Brown, 2010).

Dignum and Dignum (2020) note that the human-centered view of AI requires agents to be more aware of the social context in which they operate. Accenture Federal Services (2018) has identified human-machine collaboration trends that could reshape the way people work in the future. These include humans training AI to perform specific tasks and machines augmenting human actions in different ways.

Lauer et al. (2020) point out that in the current stage of research on human-machine collaboration, AI algorithms are not yet able to emulate human intuition, although they have made advances in cognitive intelligence. They highlight the relevance of studies investigating the ability of AI to replicate human cognitive and emotional competencies, especially with regard to judgments and decision-making (Selwyn, 2019).

In the future, the work will consist of sets of CPS with which skilled humans will have to be familiar, gaining insights on operations directly from smart machines (Lu & Weng, 2018).

Development of behavioral competencies for Industry 4.0

As the focus of Industry 4.0 is to create intelligent products and processes, it is a challenge for those involved in engineering education to tailor their programs to the kind of profile their students will need to have to meet real-world requirements.

Hecklau et al. (2017) examined the impact of digitalization on the competencies required by companies in their "Human resources management: meta-study – analysis of future competences in Industry 4.0". To identify competencies in publications focused on Industry 4.0, they used the concept of job-specific technical and behavioral competencies.

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Since 2015, the German-based research group Plattform Industrie 4.0 has been researching the competencies required for Industry 4.0 and the training needed to meet the requirements of the digitalized workplace (Federal Ministry for Economic Affairs and Energy, 2017). Siemens created the project Industrie 4.0@SPE, focusing on analyzing the changes resulting from the increasing digitalization in the world of work to adapt the content, teaching methods, knowledge, and skills of instructors working in continuing education. Systems, applications, and products (SAP) use learning platforms that can be accessed via mobile devices to enable the preparation of learning roadmaps.

Senderek and Geisler (2015) have highlighted the contribution of intelligent assistants to skills development for Industry 4.0 in work environments. Its potential to support human decision-making processes is based on their capacity to capture and combine data and provide and evaluate information about the environment. A unit of the Fraunhofer Institute in Stuttgart worked on the APPsist research project (Ullrich et al., 2016), which presents instructions for fixing machine failures on tablets, through texts and videos that demonstrate how to execute the necessary tasks. The system has a VR/AR interface that enables workers to progress according to their own pace of learning, request videos with in-depth content and skip explanations on processes they already master.

Prifti et al. (2017), from the University of Munich, have developed a competency model for Industry 4.0 with a focus on the Information System, Computer Science, and Engineering programs. The basis for the model is the Universal Competency Framework, which is centered on behavioral skills and the probability of success in the workplace. This framework is structured in three hierarchical levels, with level 1 consisting of eight major categories of competencies (Table 1), followed by competency dimensions at level 2, and behavioral competencies at level 3. It offers a structured overview of competencies, which are allocated to categories (Bartram, 2012). This structure is widely used in practice to develop competency models for specific positions or contexts (Kleindauer, 2012).

To develop their model, Prifti et al. (2017) maintained the structural relationship between the elements (levels 1 and 2) but adapted level 3. They replaced the general competencies from the framework with competencies for Industry 4.0 obtained from a literature review and focus group sessions with professors, specialists, and consultants involved in research on the subject. Table 2 presents the resulting competencies model for Industry 4.0.

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Table 1

Big eight behavioral competencies – level 1

Big eight behavioral competencies	Description
1. Supporting and cooperating	Supports and demonstrates respect in teamwork.
2. Interacting and presenting	Communicates and influences others with confidence.
3. Analyzing and interpreting	Demonstrates analytical thinking for complex problem solving and is quick to assimilate new technologies.
4. Creating and conceptualizing	Actively seeks new learning opportunities and employs broad, strategic thinking.
5. Organizing and executing	Provides services or products that meet the agreed quality standards.
6. Adapting and coping	Adapts and responds well to change and pressure.
7. Enterprising and performing	Shows understanding of business and finance and seeks out opportunities for their own career development.
8. Leading and deciding	Takes control and exercises leadership, initiates action, gives direction, and takes responsibility.

Source: Adapted from the Universal Competence Framework (Bartram, 2012).

Table 2

Model of competencies for Industry 4.0

Level 1	Level 2	Level 3		
Big eight behavioral competencies	Competency dimensions	Competencies		
		Information Systems	Computer Science	Engineering
Supporting and cooperating	Adhering to principles and values	Ethics, environmental and ergonomic awareness		
	Working well with people	Teamwork, collaboration, communication		
Interacting and presenting	Networking	Compromising, networking, customer relations		
	Influencing	Negotiation, emotional intelligence		
	Presenting information	Presenting and communicating		
Analyzing and interpreting	Writing and reporting	Technical communication, speaking/ writing skills		

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Table 2 (continuation)

Model of competencies for Industry 4.0

Level 1	Level 2	Level 3		
Big eight behavioral competencies	Competency dimensions	Competencies		
		Information Systems	Computer Science	Engineering
Analyzing and interpreting	Applying expertise and technology	Information and technology; economics extracts business value from media		
		Service orientation/ product-service offerings	Network security	
		Business process management	Information technology (IT) architecture	
		Business change management	Machine learning	
		Coordination of workflows		
			System development; technology integration	
			Mobile technologies, sensors/ embedded systems	
			Network technology, machine-to-machine (M2M) communication	
			Robotics and artificial intelligence	
			Predictive maintenance	
		Modeling and programming, big data analysis		
		Cloud computing/architectures, databases		
		Statistics/data security		
	Analyzing	Problem solving, optimization, analytical skills, cognition		

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Table 2 (conclusion)

Model of competencies for Industry 4.0

Level 1	Level 2	Level 3		
Big eight behavioral competencies	Competency dimensions	Competencies		
		Information Systems	Computer Science	Engineering
Creating and conceptualizing	Learning and researching	Lifelong learning, knowledge management		
	Creating and innovating	Innovating, creativity, critical thinking, change management		
	Formulating strategies and concepts	Business strategy, abstraction, managing complexity		
Organizing and executing	Planning and organizing	Project management, planning and organizing work, management		
	Delivering results and meeting customer expectations	Customer orientation, customer relationship management		
	Following instructions and procedures	Legislation, security, individual responsibility		
Adapting and coping	Adapting to change	Work in an interdisciplinary environment, interculturality, flexibility, open-mindedness		
	Persuading and influencing	Work-life balance		
Enterprising and performing	Achieving goals and objectives	Self-management		
	Entrepreneurial thinking	Understanding of business model, entrepreneurship		
Leading and deciding	Deciding and initiating action	Decision-making, taking on responsibility		
	Leading and supervising	Leadership		

Source: Adapted from Prifti et al. (2017).

Interestingly, most of the behavioral skills are compatible with the three programs – Information Systems, Computer Science, and Engineering –, indicating that professionals need to demonstrate a wide range of interdisciplinary competencies to work successfully in Industry 4.0. For example, engineers will have to collaborate with experts in computer science and information systems to deliver results.

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New *curriculum* guidelines for degrees in Engineering

Brazil's new National Curriculum Guidelines for Engineering programs (Resolução nº 2, 2019) are designed to raise the quality of engineering education in the country and update the delivery of this education. The processes covered in the new national *curriculum* guidelines (Table 3) are competency-based training, innovative methodologies, encouragement of innovative institutional policies, emphasis on the management of the learning process, strengthening ties with different organizations, and valuing the qualification of the faculty (Resolução nº 2, 2019).

Table 3

Processes in the new curriculum *guidelines for degrees in Engineering*

Employing competency-based training	Engineering education should be based on competencies involving the diversity of people's expectations and behaviors. Techniques should be used to transform observation into an economically viable problem formulation and problem-solving, with the application of technologies to meet user and market demands.
Adopting innovative methodologies	This implies adopting teaching methodologies that better meet the needs of the global reality, combined with developing behavioral competencies and motivating students to seek out different sources of input. The idea is to make the engineering learning process more dynamic and autonomous, engaging students in solving concrete problems that require interdisciplinary knowledge in a bid to raise the quality of teaching and reduce drop-out rates.
Encouraging innovative institutional policies	The idea is to promote a greater diversity of engineers to meet the different needs of society, such as housing, security, education, and health. The new guidelines are more flexible so that each higher education institution can structure its courses as it wishes to foster the competencies needed for the graduates of each program.
Managing the learning process	The new *curriculum* guidelines are designed to encourage the development of a culture within higher education institutions that fosters the management of competency development. This means developing academic and professional profiles that are aligned with international benchmarks and training students to work effectively in the area of engineering anywhere in the world.
Strengthening ties with different organizations	The programs should promote interactions with organizations for the development of projects of mutual interest while also encouraging the students' final-year projects to address concrete problems faced by companies.

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Table 3 (conclusion)

Processes in the new curriculum *guidelines for degrees in Engineering*

Valuing the qualification of professors	Professors should be encouraged to train in new teaching/learning methods and strategies, develop their pedagogic and academic management skills, strike a balance between functional incentives, academic incentives, research funding, outreach, and teaching activities and involve business professionals in academic activities.

Source: Resolução nº 2 (2019).

METHODOLOGY

The research has a exploratory and qualitative nature. Exploratory research is carried out when the chosen topic is little explored, making it hard to formulate precise hypotheses (Gil, 2008). Qualitative research is interpretive as the researcher interprets the data (Creswell, 2007).

Design Thinking (Brown, 2010) was applied iteratively to identify and summarize ideas for designing the functionalities of the machine AI-engineer collaboration model. First, a brainstorming session was held with experts in the human factor, product design, and engineering processes, and, subsequently, with experts in intelligent interfaces, VR, and AR.

Once the functionalities had been decided, the engineer-machine collaboration model was formulated. This included cognitive modeling of the engineer's critical thinking to train the AI algorithm, integrating Paul and Elder's (2002) and Paul et al. (2006) critical thinking/logical reasoning model/checklist with Riley's (1989) model.

The implementation of the competency model for Industry 4.0 (Prifti et al., 2017), interviews with leaders from the School of Chemistry and Polytechnic School of the UFRJ addressing their planning for the implementation of the new national *curriculum* guidelines for engineering programs (Resolução nº 2, 2019), and the GRADE approach (Balshem et al., 2011) were used to assess the quality of evidence of behavioral skills for Industry 4.0 in the undergraduate programs.

UFRJ was chosen because of its long, internationally recognized tradition in engineering education. The School of Chemistry offers programs in Chemical, Bioprocess, and Food Engineering, as well as joint programs with the Polytechnic School and/or the Alberto Luiz Coimbra Institute for Graduate Studies and Research in Engineering (Petroleum, Control and Instrumentation, and Environmental Engineering). The Polytechnic School offers 13

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degree programs in Electrical, Electronic and Computing, Mechanical, Metallurgical, Materials, Control and Automation, Computing and Information, Petroleum, Naval and Ocean, Nuclear, Production, Environmental, and Civil Engineering.

Data were collected from interviews with the deputy director of undergraduate studies of the Chemistry School and the director of the Polytechnic School, with questions that focused on their plans for the implementation of the new processes in the new *curriculum* guidelines for Engineering degree programs (Table 3). According to Gil (2008, p. 11), "different types of interviews can be used according to how structured they are. The most structured interviews are the ones that predetermine, to a greater degree, the answers to be obtained".

The first stage of implementing the model of competencies for Industry 4.0 proposed by Prifti et al. (2017) consisted of transcribing and analyzing the content to extract relevant information. Next, the process of grouping the information into the eight major competency categories (level 1) was started. After this, the GRADE approach (Balshem et al., 2011) was applied in individual sessions to assess the quality of evidence (Table 4) of the relevant information in the category. Finally, maintaining the same structure as the Prifti et al. (2017) model (Table 2), this evaluation of the quality of evidence performed for level 1 was repeated through to level 3, extracting the relevant behavioral competencies for engineering training regarding Industry 4.0.

Table 4

Quality levels of evidence and definition

Level of quality of evidence	Definition
High	High level of confidence in the quality of the evidence.
Moderate	Moderate level of confidence in the quality of the evidence: estimate is very similar to reality but could diverge.
Low	Low level of confidence in the quality of the evidence: estimate may diverge from reality.
Very low	Very low level of confidence in the quality of the evidence: estimate may diverge substantially from reality.

Source: Balshem et al. (2011).

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RESULTS AND DISCUSSION

The model for engineer-machine (AI application) collaboration, based on the design-thinking-inspired brainstorming sessions with specialists described above, illustrates the development of the engineer's critical analysis and decision-making competencies while the machine searches for and processes information and performs simulations. The conception of the functionalities of the collaboration model is illustrated in Figure 1, in which two agents (engineer and AI) communicate through intelligent interfaces – voice, gesture, facial expression and body language recognition, and eye tracking –, depending on the context. In order to exemplify engineer-machine collaboration, a concrete case of product development and decision-making competency development has been chosen, with a focus on new materials:

- Engineer: requests search for products similar to the one they want to develop.
- AI: provides the design, lists, and types of materials from similar product(s).
- Engineer: inputs the thermal conductivity and elasticity parameters for the material.
- AI: provides options for materials, suppliers, and test videos with a similar product.
- Engineer: explores features of simulation using VR and AR technologies, gaining insights into the material's characteristics and product handling. With VR, they can develop prototypes and handle the product or components, and with AR, they can inspect component assembly.

The modeling of the engineer's cognitive process to train the AI algorithm was based on the critical thinking model (Paul & Elder, 2002) presented in Figure 2 and *The thinker's guide to engineering reasoning* (Paul et al., 2006).

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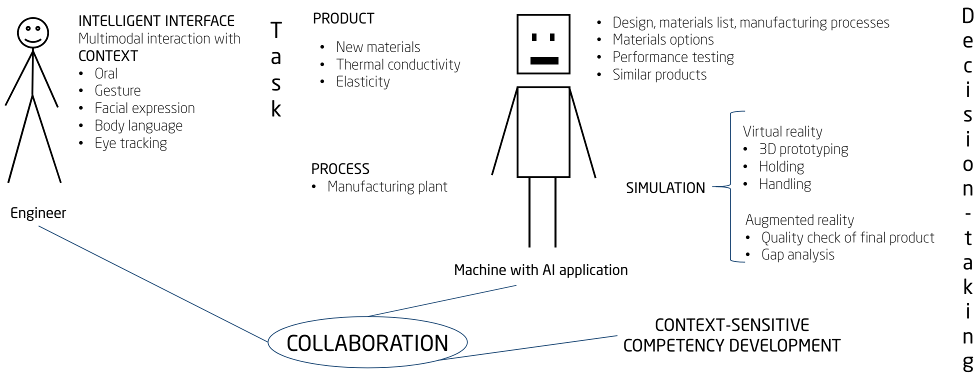
Figure 1

Functionalities of the human-machine (AI) collaboration model



Source: Elaborated by the authors.

Figure 2

Critical thinking model

Intellectual patterns	
Clarity	Range
Accuracy	Precision
Relevance	Depth
Logic	Equity

Elements of reasoning	
Purpose	Information
Problem	Concepts
Suppositions	Inferences
Point of view	Implications

Source: Adapted from Paul and Elder (2002).

Paul et al. (2006) applied the critical thinking model to engineering (Figure 2), offering instructions to guide engineers in their logical reasoning and critical thinking: 1. express the purpose clearly; 2. ask the right questions to solve the problem; 3. make assumptions and suppositions; 4. consider the stakeholders' points of view; 5. use valid data and information from reliable sources; 6. use alternative concepts with precision; and 7. ascertain the implications of inferences and interpretations. An example of the

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checklist would be as follows: 1. the engineer states the purpose, distinguishes it from other related purposes and monitors its progress periodically; 2. the engineer sets about solving a specific problem, defining it clearly, representing it in different ways to ascertain its scope and whether it requires reasoning from different hypotheses or points of view, and so on, for all the elements of reasoning.

The model and its functionalities (Figure 1) were applied to Paul et al.'s (2006) checklist to model AI training (Table 5). The engineer's actions are described on the left, and the machines are on the right. For example, in the first line, the engineer defines the problem and expresses the objective – they make a decision regarding the development of new products. The machine checks for permission and infers the engineer's intent. Next, the engineer asks questions (*e.g.*, "What type of material is most suitable for the top and bottom coating of the product?"), and the machine receives and processes the information and displays a drawing and a list of materials.

Table 5

Model for AI training by engineer

Engineer	Machine (AI application)
Defines problem and expresses objective: makes a decision regarding the development of new products.	Checks for permission and infers the engineer's intention and knowledge.
Expresses questions: what types of material are most suitable for the top and bottom coatings of the product?	Receives and processes information – presents a drawing and list of materials.
Provides information: conductivity/elasticity parameters of the material for the upper and lower coating of the product cylinder.	Processes information and offers alternatives for decision-making. Presents options of materials, suggesting which is best. Presents a video with a performance test, similar product(s), and suppliers and awaits approval from the engineer before taking further action.
Perceives the machine's behavior, perceives the information presented and monitors and requests information: VR simulation/3D prototyping of product to gain insights on its handling and performance; quality simulation of the complete product using AR to check for potential gaps.	Does a simulation, generates a 3D prototype of the product and advises the engineer as to the correct way to handle the product.

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Table 5 (conclusion)

Model for AI training by engineer

Engineer	Machine (AI application)
Checks inferences: production cost.	Presents a holographic projection of the production area, monitors movements of other production workers and requests collaboration.
Makes a decision.	

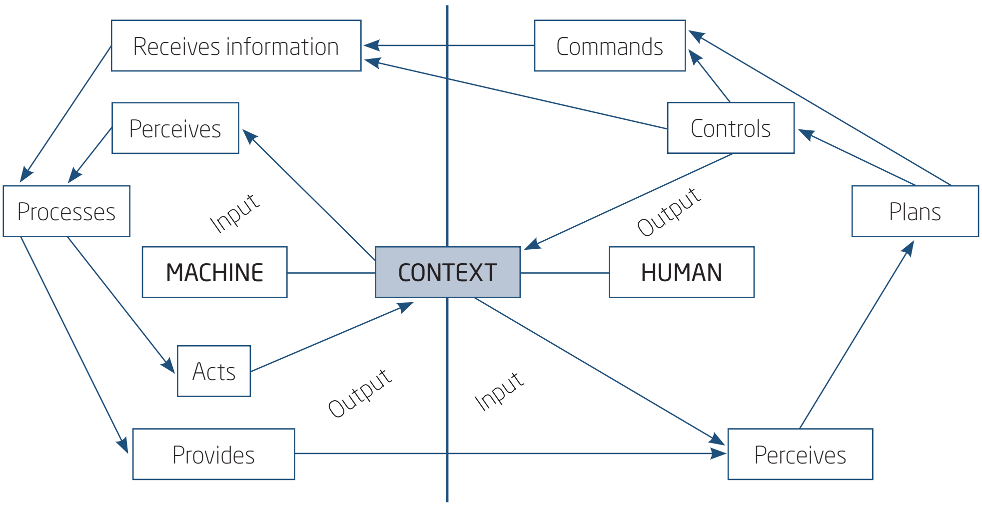
Source: Elaborated by the authors.

The steps proceed in succession until a decision is made. The engineer draws on their own logical reasoning and critical analysis to train the machine (AI application), which expands its memory, seeks and processes information, does simulations, suggests actions and provides support for decision-making.

The model for AI training by the engineer (Table 5) was then integrated into an adaptation of Riley's (1989) model of the information flow in human-machine interactions (Figure 3).

Figure 3

Model of information flows in human-machine interactions



Source: Adapted from Riley (1989).

Finally, the AI training model (Table 5) was incorporated into an adapted version of Riley's (1989) model of information flows in human-machine

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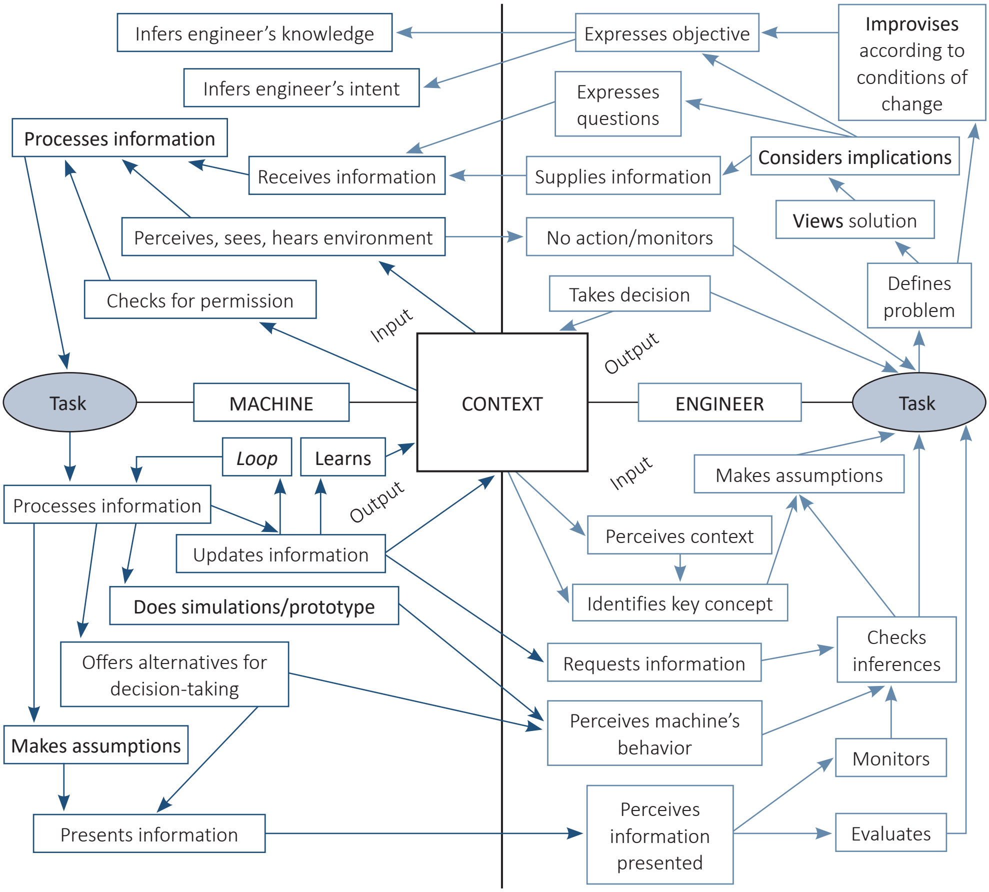
interactions (Figure 3) to generate the model of engineer-machine collaboration with an AI application (Figure 4).

Figure 4

Model of human-machine collaboration with AI application



Source: Elaborated by the authors.

This engineer-machine collaboration model encompasses the machine (left), the engineer (right), and the context (middle). In this model, context means the various intelligent interfaces – voice, gesture, facial expression, body language recognition, and eye tracking – used in the engineer-machine (AI application) interaction. In the three loops (engineer-context, machine-context, and engineer-machine), information from the collaboration between the two agents is processed, with the context providing the machine and engineer with information, the machine and engineer providing the context with information in the form of actions, and a loop for exchanges of infor-

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mation between the engineer and the machine. The machine searches for and processes information and performs simulations, while the engineer employs logical reasoning, critical analysis, and decision-making skills.

An evaluation of the quality of evidence of the development of behavioral competencies for Industry 4.0 in the Engineering degree program of the UFRJ is presented in Table 6. The eight main competency categories from Prifti et al.'s (2017) model (Table 2) are described in column 1, relevant information extracted from the leaders' responses are in column 2, and evaluations of the quality of evidence of the relevant information are in the respective categories in column 3.

Table 6

Quality of evidence of the eight main categories of competencies

Great eight competencies	Relevant information extracted from interviews with leaders from the schools of engineering of UFRJ	Level of quality of evidence
1. Supporting and cooperating	*[Our] alliances have been with CREA [engineering council], the Engineers' Club, and companies. The university's portfolio of alliances comes from research projects and the hiring of students by partner companies, which see the university as an opportunity to publicize their selection processes and need students to fill their vacancies.*	**Moderate** confidence in the quality of evidence, but the reality could be different.
2. Interacting and presenting	*A plan to expand our interactions would be important to showcase the students' true profile. This is being planned by the coordinators of the internships, and once our partner companies have been analyzed, it will be possible to prospect other companies.*	**Low** confidence in the quality of evidence, the reality may be substantially different.
3. Analyzing and interpreting	*As for Industry 4.0 and AI in engineering education, this means taking action to include, in the courses taught, scientific computing and tools that can introduce the students to this expertise. The actions should be executed by the faculty, provided they are properly incorporated into the course syllabuses and the descriptions of the courses that use these approaches.* *Many tasks that engineers perform aren't core engineering activities, which have to do with thinking about systems, creating and proposing solutions, identifying and analyzing problems, and innovating. In other words, everything a machine can do is not what an engineer does. In their continuing education, engineers should aim to be like a conductor, conducting an orchestra of different types of expertise, and every virtuoso conductor begins being an expert in one musical instrument (degree in Engineering).*	**Moderate** confidence in the quality of evidence, but the reality could be different.

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Table 6 (continuation)

Quality of evidence of the Eight Main categories of competencies

Great eight competencies	Relevant information extracted from interviews with leaders from the schools of engineering of UFRJ	Level of quality of evidence
4. Creating and conceptualizing	*Engineering is, by definition, multidisciplinary. It's been broken down by an excess of the scientific method applied to the professional area – the optimal method for research but really bad for doing a project (design). We have to get back to the method of developing solutions for problems, identifying problems, studying problems, identifying requirements, devising solutions, scaling up projects (design), studying their feasibility (now with multiple criteria, sustainable), and detailing their execution.* The curriculum *reform is moving in this direction.*	**Moderate** confidence in the quality of evidence, but the reality could be different.
5. Organizing and executing	*There are a lot of methodologies to bring about a reformulation of the teaching and training methods for these professionals, always maintaining the relationship between practice and theory: active methodologies, integrated projects, flipped classroom, use of blogs, robotics, Moodle, modeling, videos, forums, group problem-solving, workshops.*	**Low** confidence in the quality of evidence, the reality may be substantially different.
6. Adapting and coping	*The students who drop out of the program are the ones who are extremely intelligent, and so they stand out, even on a course that wasn't their first choice. When they realize this, they drop out in search of their real aptitudes. I think the main way of measuring a student's success during an Engineering program is whether they enter the market, whether it is through internships during the program or even getting a job after completing the program. Today, about 80% of our students take an internship in companies, and at the end of the program, 70% are employed, and 10% do graduate studies.* *It's become standard practice to analyze the student's average grade, which is actually valued more by the professors than by the market, which evaluates other skills.*	**Moderate** confidence in the quality of evidence, but the reality could be different.
7. Enterprising and performing	No evidence.	

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Table 6 (conclusion)

Quality of evidence of the Eight Main categories of competencies

Great eight competencies	Relevant information extracted from interviews with leaders from the schools of engineering of UFRJ	Level of quality of evidence
8. Leading and deciding	*As for encouraging students to monitor their own learning/ performance throughout the program, it's tricky. If it isn't very clearly structured, pedagogically and psychologically speaking, it can make them frustrated and even hinder the process. I think the best thing is to oversight together with a professor because then the student can understand their real potential according to what stage of life they're at and what their current needs are.*	**Low** confidence in the quality of evidence, the reality may be substantially different.

Source: Elaborated by the authors.

Following the structure of Prifti et al.'s (2017) model (Table 2), the evaluation of the quality of evidence at level 1 was extended up to level 3. In this study, only the competencies for Industry 4.0 related to engineering education were extracted, as shown in Figure 5.

The results indicate that most behavioral skills were attributed to a *moderate* level of confidence (light blue). There is room to strengthen and diversify relationship networks through the development of joint projects between academia and the business sectors. The assimilation and application of digital technologies could lead to more opportunities for training in solving complex problems. This would call for a curricular redesign focused on continuous learning, collaboration with multidisciplinary teams, creation of business strategies, flexibility, leadership, innovation, creativity, and mastery of oral and written communication for developing, prototyping, testing, and presenting solutions of value to customers and society. The issue of student drop-out is critical because, as pointed out, students may stand out academically and still choose to leave the program. The pressure for results could be addressed by getting students involved in team projects focused on real-world problems. The new *curriculum* presents opportunities for this, potentially enhancing results in the short term (one semester or 120 days) if resources (accumulated knowledge, talent, and teaching experience), processes (governance, infrastructure, laboratories, research), and values (student learning as a priority) are properly mobilized.

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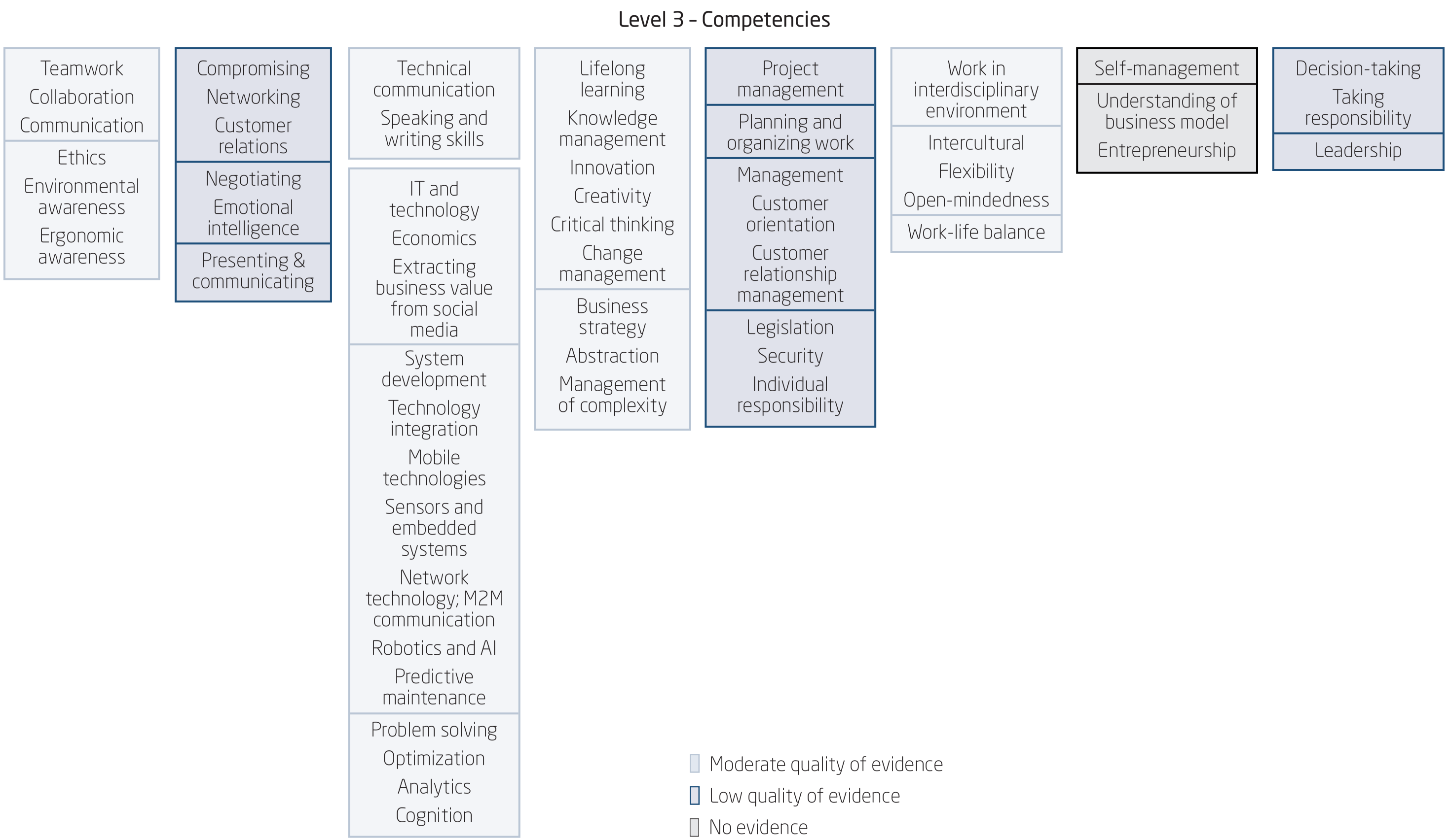
Figura 5

Quality of evidence of behavioral competencies for Industry 4.0 in the Engineering degree programs of UFRJ



Source: Elaborated by the authors

With regard to the competencies with a *low* level of confidence (dark blue), network expansion, with new partnerships between academia and business professionals, could provide opportunities to improve negotiating skills, oral/written communication, and the ability to put across an argument or point of view. Being committed and organized is a prerequisite for making things happen with a high standard of quality. It takes a lot of practice for students to learn how to take ownership of their learning process, learn to give directions, focus, take the initiative, and take on responsibility. Similarly, it poses a big challenge for professors as they take on new roles and adopt new methodologies to train students in the kinds of situations the students will experience in their professional life.

No evidence was found (grey) for entrepreneurship, understanding of business models, or self-management. One way to develop such competencies would be to seek out external partners who could give advice on how to develop teaching strategies for them in the medium term (one academic year or 240 days). No behavioral competencies with *strong* evidence of quality were identified.

CONCLUDING REMARKS

One of the biggest challenges to emerge with Industry 4.0 is the training of engineers qualified to work effectively in workplaces reconfigured by this new paradigm. Training in the necessary skills should be given when prospective engineers are still taking their first degree. This article seeks to answer the following research question: "How can engineering professionals and students be prepared for Industry 4.0?".

The subjective evaluation used in this study to assess the quality of evidence of behavioral competencies based on answers to questions given by leaders of engineering schools has some limitations. Nonetheless, the GRADE approach used here provides a robust framework for the analysis of judgments.

This study contributes to the literature by providing a starting point for more in-depth discussions and debates on the training of engineers for smart work environments in the context of the exponential growth of unstructured data. It is expected that this article helps to raise educators' awareness as to the importance of designing *curricula* aimed at the development of behavioral skills for Industry 4.0, so that Engineering students can successfully transition from the classroom to the workplace with the ability to perform more strategic functions.

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Future studies could apply a similar methodology to engineering schools in other Brazilian states. Quantitative research to compare evidence of behavioral competency development for Industry 4.0 between federal and private universities could also provide valuable insights for forums to discuss engineering education and for defining what new functions engineers need to have when working in smart environments.

REFERENCES

Acatech (2016). Innovation potential of human-machine interaction. In acatech (Ed.), *Innovationspotenziale der Mensch-Maschine-Interaktion* (*acatech IMPULSE*). Herbert Utz Verlag. https://en.acatech.de/publication/innovation-potential-of-human-machine-interaction/download-pdf/?lang=en_excerpt

Accenture Federal Services (2018). *Process reimagined: Together, people and AI are reinventing business processes from the ground up*. https://www.accenture.com/_acnmedia/PDF-80/Accenture-Federal-Services-Process-Reimagined. pdf

Aggarwal, C. C. (2018). *Neural networks and deep learning*. Springer. https://doi.org/10.1007/978-3-319-94463-0

Bahceci, E. (2016). Discussion of human-computer interaction and its relevance to natural language procession in the context of IPAs.

Balshem, H., Helfand, M., Schünemann, H. J., Oxman, A. D, Kunz, R., Brozek, J., Vist, G. E., Falck-Ytter, Y., Meerpohl, J., Norris, S., & Guyatt, G. H. (2011). GRADE guidelines: 3. Rating the quality of evidence. *Journal of Clinical Epidemiology*, *64*(4), 401–406. https://doi.org/10.1016/j.jclinepi.2010.07.015

Bartram, D. (2012). The SHL Universal Competency Framework [White paper]. *The CEB Talent Measurement Solution*. https://connectingcredentials.org/wp-content/uploads/2015/02/The-SHL-Universal-Competency-Framework.pdf

Brown, T. (2010). *Design Thinking: Uma metodologia poderosa para decretar o fim das velhas ideias*. Elsevier, Alta Books.

Brühl, V. (2015). *Industrie 4.0 Wirtschaft des 21. Jahrhunderts: Herausforderungen in der Hightech-Ökonomie*. Springer Fachmedien Wiesbaden.

Creswell, J. W. (2007). *Projeto de pesquisa: Método qualitativo, quantitativo e misto*. Artmed.

Dale, R. (2016). The return of the chatbots. *Natural Language Engineering, 22*(5), 811–817. https://doi.org/10.1017/S1351324916000243

Dignum, V., & Dignum, F. (2020, May 9–13). Agents are dead. Long live agents! *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*. https://dl.acm.org/doi/abs/10.5555/3398761.3398957

Edwards, L., & Veale, M. (2017). Slave to the algorithm? Why a "Rigth to an Explanation" is probably not the remedy you are looking for. *Duke Law and Technology Review*, 18–84. https://scholarship.law.duke.edu/dltr/vol16/iss1/2

Ertel, W. (2017). *Introduction to artificial intelligence*. Springer. https://doi.org/10.1007/978-3-319-58487-4

Farooq, U., & Grudin, J. (2016). Human-computer integration. *Interactions, 23*(6), 26–32. https://doi.org/10.1145/3001896

Federal Ministry for Economic Affairs and Energy (2017). Shaping the digital transformation within companies – Examples and recommendations for action regarding basic and further training. https://www.plattform-i40.de/IP/Redaktion/EN/Downloads/Publikation/digital-transformation-training.pdf?__blob=publicationFile&v=5

Gil, A. C. (2008). *Métodos e técnicas de pesquisa social*. Atlas.

Hecklau, F., Orth, R., Kidschun, F., & Kohl, H. (2017, December 11–12). Human resources management: Meta-study – Analysis of future competences in Industry 4.0. In M. Rich (Ed.), *Proceedings 13th European Conference on Management Leadership and Governance (ECMLG)* (pp. 163–174). Academic Conferences and Publishing International.

Hermann, M., Pentek, T., & Otto, B. (2016, January 5–8). Design principles for Industry 4.0 Scenarios: A literature review. *49th Hawaii International Conference on System Sciences (HICSS)*. https://doi.org/10.1109/HICSS.2016.488

Jurafsky, D., & Martin, J. (2020). *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition* (3rd ed.). Prentice hall.

Kleindauer, R., Berkovich, M., Gelvin, R., Leimeister, J. M., & Krcmar, H. (2012). Towards a competency model for requirements analysts 395 1.2. *Information System Jornal*, 475–503.

ISSN 1678-6971 (electronic version) • RAM, São Paulo, *24*(5), eRAMR230084, 2023
https://doi.org/10.1590/1678-6971/eRAMR230084.en

Lauer, T., Welsch, R., Abbas, S., & Henke, M. (2020). Behavioral analysis of human-machine interaction in the context of demand planning decisions. In T. Ahram (Eds.), *Advances in artificial intelligence, software and systems engineering* (pp. 130–141). Springer. https://doi.org/10.1007/978-3-030-20454-9_13

Lu, H.-P., & Weng, C.-I. (2018). Smart manufacturing technology, market maturity analysis and technology roadmap in the computer and electronic product manufacturing industry. *Technological Forecasting & Social Change, 133*, 85–94. https://doi.org/10.1016/j.techfore.2018.03.005

Marra, R. M., Kim, S. M., Plumb, C., Hacker, D. J., & Bossaller, S. (2017). Beyond the technical: Developing lifelong learning and metacognition for the engineering workplace [Paper ID #17712]. *American Society for Engineering Education*.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence, 267,* 1–38. https://doi.org/10.1016/j.artint.2018.07.007

Organisation for Economic Cooperation and Development (2017). Computers and the future of skills demand. *Educational Research and Innovation*. https://doi.org/10.1787/9789264284395-en.

Organisation for Economic Cooperation and Development (2018). The future of education and skills. *Education 2030*. http://www.oecd.org/education/2030/oecd-education-2030-position-paper.pdf.

Paul, R., & Elder, L. (2002). *Critical thinking: Tools for taking charge of your professional and personal life*. Prentice-Hall.

Paul, R., Niewoehner, R., & Elder, L. (2006). *The thinker's guide to engineering reasoning: Based on critical thinking concepts and tools*. Foundation for Critical Thinking.

Pricewaterhouse Coopers-PwC. (2017). *Digital Factories 2020: Shaping the future of manufacturing*. https://www.pwc.de/de/digitale-transformation/digital-factories-2020-shaping-the-future-of-manufacturing.pdf

Prifti, L. Knigge, M., Kienegger, H., Krcmar, H. (2017). A competency model for Industrie 4.0 employees. In J. M. Leimeister & W. Brenner (Hrsg.), *Proceedings der 13. Internationalen Tagung Wirtschaftsinformatik* (pp. 46–60). St. Gallen. https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1003&context=wi2017

ISSN 1678-6971 (electronic version) • RAM, São Paulo, *24*(5), eRAMR230084, 2023
https://doi.org/10.1590/1678-6971/eRAMR230084.en

Resolução nº 2, de 24 de abril de 2019 (2019). Institui as Diretrizes Curriculares Nacionais do Curso de Graduação em Engenharia. http://portal.mec.gov.br/index.php?option=com_docman&view=download&alias=112681-rces002-19&category_slug=abril-2019-pdf&Itemid=30192

Riley, V. (1989). A general model of mixed-initiative human-machine system. *Proceeding of the Human Factors Society Annual Meeting, 33*(2), 124–128. https://doi.org/10.1177/154193128903300227

Roth, A. (2016). Industrie 4.0 – Hype oder revolution? In A. Roth (Ed.), *Einführung und Umsetzung von Industrie 4.0: Grundlagen, Vorehensmodell und Use Cases aus der Praxis* (pp. 1–15). Gabler Verlag.

Sabella, R. (2018, October 2). What is a design-physical system? Ericson Blog. www.ericsson.com/en/blog/2019/12/design-physical-systems-technology-trend.

Selwyn, N. (2019). *Should robots replace teachers?: AI and the future of education*. Wiley.

Senderek, R., & Geisler, K. (2015, September 1st). Assistenzsysteme zur Lernunterstützung in der Industrie 4.0. In S. Rarhmayer & H. Pongratz (Eds.), *Proceedings of DeLFI Workshops co-located with 13th e-Learning Conference of the German Computer Society* (pp. 36–46). http://ceur-ws.org/Vol-1443/paper14.pdf

Sonntag, D. (2015). *Intelligent user interfaces will introduce you to the design and implementation of Intelligent User Interfaces (IUIs)*. German Research Centre for Artificial Intelligence (DFKI). dfki.de/~sonntag/courses/WS14/IUI.html

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S., Kamar, E., Kraus, S., Leyton-Brown, K., Parkes, D., Press, W., Saxenian, A., Shah, J., Tambe, M., & Teller, A. (2016). *Artificial intelligence and life in 2030*: *One hundred year study on artificial intelligence*. Stanford University. http://ai100.stanford.edu/2016-report

Ullrich, C., Aust, M., Dietrich, M., Herbig, N., Igel, C., Kreggenfeld, N., Prinz, C., Raber, F., Schwantzer, S., & Sulzmann, F. (2016, September 11). APPsist Statusbericht: Realisierung einer Plattform für Assistenz- und Wissensdienste für die Industrie 4.0. In R. Zender (Hrsg.), *Proceedings of DeLFI Workshops 2016 co-located with 14th e-Learning Conference of the German Computer Society (DeLFI 2016)* (pp. 174–180). http://ceur-ws.org/Vol-1669/WS6_1_093_Paper.pdf

ISSN 1678-6971 (electronic version) • RAM, São Paulo, *24*(5), eRAMR230084, 2023
https://doi.org/10.1590/1678-6971/eRAMR230084.en

Wang, W., & Siau, K. (2019). Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity: A review and research agenda. *Journal of Database Management*, *30*(1), 61–79. https://doi.org/10.4018/JDM.2019010104

Weyer, S., Schmitt, M., Ohmer, M., & Goreck, D. (2015). Towards Industry 4.0 – Standardization as the crucial challenge for highly modular multivendor production systems. *IFAC-PapersOnLine*, *48*(3), 579–584. https://doi.org/10.1016/j.ifacol.2015.06.143

Zhuang, Y.-T., Wu, F., Chen, C., & Pan, Y.-H. (2017). Challenges and opportunities: From big data to knowledge in AI 2.0. *Frontiers of Information Technology & Electronic Engineering*, *18*, 3–14. https://doi.org/10.1631/FITEE.1601883

ISSN 1678-6971 (electronic version) • RAM, São Paulo, *24*(5), eRAMR230084, 2023
https://doi.org/10.1590/1678-6971/eRAMR230084.en