Education 4.0 : défi de la révolution digitale dans l'actualisation des connaissances et compétences des cursus de génie des procédés

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Résumé

Les technologies de gestion des données, les techniques de communication et de connexion et les innovations de rupture de l'industrie 4.0 des procédés impliquent de disposer d'une population compétentes d'opérateurs, de techniciens et d'ingénieurs maîtrisant la mise en œuvre et les conséquences de ces technologies numériques. Cet article propose d'examiner le curriculum d'enseignement en formation initiale des compétences actualisées requises des acteurs du domaine industriel du génie chimique et du génie des procédés pour s'adapter aux besoins industriels et aux évolutions sociétales générés par la disruption des technologies numériques.

Une première recommandation immédiate et unanime consiste à mutualiser les langages actuellement disjoints entre la communauté du génie des procédés et celle des experts de l'intelligence artificielle et de la numérisation en termes de compréhension mutuelle réciproque.

Une revue des nouvelles compétences et connaissances nécessaires pour s'adapter à l'Industrie 4.0 est ensuite présentée. Un cadre pédagogique des principales composantes de l'Education 4.0 est retenu. Il incorpore stratégiquement diverses compétences telles que les mathématiques, la modélisation, l'IA, la simulation, l'IoT, la technologie de l'information, la simulation, les réseaux neuronaux, les mégadonnées, la robotique, l'informatique en nuage, l'apprentissage automatique, l'apprentissage profond et la fabrication additive pour l'expérience d'apprentissage, afin de répondre aux exigences actuelles de l'Industrie 4.0. Une déclinaison pratique applicable et acceptable de ce cadre est formulée en fonction de la pertinence relative de chaque famille de composantes évaluée en échelle de Blum sur la base des dires d'experts. A titre d'exemple, il est ainsi possible d'obtenir pour la compétence « maîtrise des données » une représentation schématique détaillée des aptitudes et compétences correspondantes.

Une revue des expériences d'introduction des méthodes d'enseignement de la science des données dans des cursus de génie chimique et de génie des procédés est rapportée. Deux propositions d'application à des exemples élargis à la composante IA dans les départements de génie chimique des Universités de Columbia (USA) et de Leuwen (B) sont détaillés.

Le génie chimique et la sécurité des procédés sont des sujets interdisciplinaires interconnectés. En tant que tel, un programme complet de sécurité des procédés inclus dans un cursus de génie chimique devrait couvrir un large éventail de sujets, depuis les phénomènes physiques et chimiques de base et les opérations unitaires jusqu'aux systèmes complexes et de plus en plus automatisés, conçus et exploités par l'homme. Les méthodes et techniques classiques d'analyse et d'évaluation des risques sont traditionnellement utilisées dans l'application de bonnes pratiques d'évaluation qualitative, semi-quantitative et quantitative. Toutefois, ces méthodes conventionnelles ont leurs limites. L'intégration de la dynamique des risques, associée à des informations récentes et précises, dans ces méthodes d'évaluation est donc aujourd'hui une nécessité pour sensibiliser les opérateurs 4.0 et les différentes parties prenantes aux exigences de la sécurité des procédés 4.0. Il est proposé que le contenu pédagogique actualisé se limite à la contribution de la simulation, des réseaux bayésiens et de la logique floue à la complétude dynamique des méthodes classiques d'analyse des risques.

Enfin, la révolution numérique 4.0 a également généré une variété d'outils pédagogiques numériques. Quelques exemples d'applications pédagogiques limitées aux deux supports d'enseignement que sont le jumeau numérique et l'apprentissage automatique sont discutés.

Education 4.0: the challenge of the digital revolution in updating the knowledge and skills of chemical and process engineering curricula

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Abstract

Data management technologies, communication, and connection techniques, and the disruptive innovations of Industry 4.0 processes imply a skilled population of operators, technicians, and engineers proficient in the implementation and consequences of these digital technologies.
This article examines the curriculum used in initial training to teach the up-to-date skills required by the actors in the industrial field of chemical and process engineering to adapt to industrial needs and societal changes generated by the disruption of digital technologies.
A first immediate and unanimous recommendation is to mutualize the currently disjointed languages between the chemical and process engineering community and that of artificial intelligence and digitization experts, in terms of mutual reciprocal understanding.
A review of the new skills and knowledge needed to adapt to Industry 4.0 is then presented. A pedagogical framework of the main components of Education 4.0 is retained. It strategically incorporates diverse skills such as mathematics, modelling, artificial intelligence (AI), simulation, internet of things (IoT), information technology, simulation, neural networks, mega data, robotics, cloud computing, machine learning, deep learning, and additive manufacturing for the learning experience, to respond to today's Industry 4.0 requirements. A practical, applicable, and acceptable version of this framework is formulated according to the relative relevance of each family of components, assessed on a Blum scale based on expert opinion. By way of example, a detailed schematic representation of data literacy skills and competencies can be obtained for the "data management" component.
A review of experiences of introducing data science teaching methods into chemical and process engineering curricula is reported. Two proposals for application to examples extended to the AI component in the chemical engineering departments of the Universities of Columbia (USA) and Leuwen (B) are detailed.
Chemical engineering and process safety are connected interdisciplinary subjects. As such, a comprehensive syllabus in process safety included in a chemical engineering curriculum should cover a wide range of topics, from basic physical and chemical phenomena and unit operations to complex and increasingly automated systems, designed and operated by humans. Classical risk analysis and assessment methods and techniques are traditionally used in the application of good qualitative, semi-quantitative, and quantitative assessment practices. However, these conventional methods have their limitations. The inclusion of risk dynamics, in conjunction with recent and accurate information, in these assessment methods is therefore now a necessity to make 4.0 operators and various stakeholders aware of the requirements of process safety 4.0. It is proposed that up-to-date pedagogical content should be limited to the contribution of simulation, Bayesian networks, and fuzzy logic to the dynamic completeness of classical risk analysis methods.
Finally, the 4.0 digital revolution has also generated a variety of digital teaching aids. Some pedagogical application examples limited to the two teaching aids Digital Twin and Machine learning are discussed.

Article

1 – Introduction

The emergence and consolidation of Industry 4.0 processes result from the implementation of several categories of digital technologies such as data management, communication and interconnection applications, and disruptive innovations. Growing awareness of sustainability is prompting the chemical industry to rethink its processes, looking for ecological alternatives to minimize their impact on the environment and preserve resources. Thanks to optimized data management systems, validated Artificial Intelligence (AI) models, and multifunctional algorithms, digital transformation becomes a process of change that offers chemical and process industries significant opportunities to adopt innovative and sustainable practices in their daily operations.

The importance of digital technology in the work of chemical and process engineers is no longer in question. The lack of digital culture and adequate training has been identified as a major challenge by the majority of companies (Horbez D., 2019). Indeed, handling, connection, analysis, interpretation, presentation, and utilization of data are seldom topics in non-data science curricula. The integration of new digital technologies therefore requires the development of new skills or the enhancement of existing ones. As a result, the basic training of future chemical and process engineers will have to reinforce this dimension.

This article aims to promote changes in the content of initial training courses in chemical and process engineering, to adapt to industrial needs and changes in society generated by the disruption of digital technologies. The first section reviews the new skills and knowledge needed to adapt to the industrial requirements and societal changes generated by the disruption of digital technologies. The second illustrates their application, in part by updating the content of the process safety curriculum. The final section highlights some deliberately limited examples of potential digital teaching aids.

2 – Review of the new knowledge and skills involved in digitalization

Numerical methods now make it possible to describe complex, often highly coupled phenomena, and provide complementary solutions for the analysis, modelling, and extrapolation of observed phenomena. Modelling and simulation have a strong presence, as they make data a fundamental element in understanding and mastering all digital technologies, in addition to the basic knowledge specific to the field of chemical and process engineering. The processing of mega data (Big Data) also announces a major evolution in the chemical and process engineering profession. Last but not least, AI and its associated technologies cannot be left out of the chemical and process engineer's baggage. In this complex situation, how can we sketch out the evolution of the content of chemical and process engineering courses to adapt to industrial needs and societal changes?

21- Framework of Education 4.0 components for Industry 4.0

According to De Souza, A.S.C. and Debs, L., (2024) and similarly to the steps of the industrial revolution from Industry 1.0 to Industry 4.0, Figure 1 shows the timeline and the key points of education transformations from Education 1.0 to Education 4.0.

The concept of Education 4.0 defines a transformation of education due to technological change, with a focus on the changing environment of Industry 4.0. The authors emphasized that Education 4.0 was the solution to meeting the demands arising from Industry 4.0. They recognized the importance of preparing the workforce to manage digital technologies and new industrial production methods.

The literature describes different qualitative teaching frameworks that the impact of digitization changes implies. Feise, H.J. and Schaer, E. (2021) reported a pedagogical synthesis of digitalized chemical engineering mastery. EFCE’s Working Party Education proposes a model that meets the recommendations of the Bologna Process (EFCE, 2020). The European Network for Accreditation of Engineering Education (ENAEE, 2024) manages the database of EUR-ACE ® accredited engineering programs describing the knowledge, understanding, skills, and abilities expected of the engineering profession. Process Net (2018), an initiative of Dechema and VDI-GVC in Germany, is a platform describing the qualifications framework and recommendations for chemical engineering, process engineering, and bioengineering programs. The Commission des Titres d’Ingénieur analysed the results of the digital focus survey in engineering schools, to address the digital transition and to evolve the CTI References and Orientations referential (Jollydig, A.M. and Schmidt, S. 2020).

Reporting on the exploitation of the results of a framed bibliometric study, Chakraborty, S. et al. (2023) proposed a synthesis of the main components corresponding to the requirements of Industry 4.0 to form an Education 4.0 database, illustrated in Figure 2. These authors consider Education 4.0 to be an educational framework, which strategically incorporates various skills such as mathematics, modelling, AI, simulation, IoT, information technology, simulation, neural networks, mega data, robotics, cloud computing, machine learning, deep learning, and additive manufacturing, for the learning experience, to meet the current requirements of Industry 4.0.

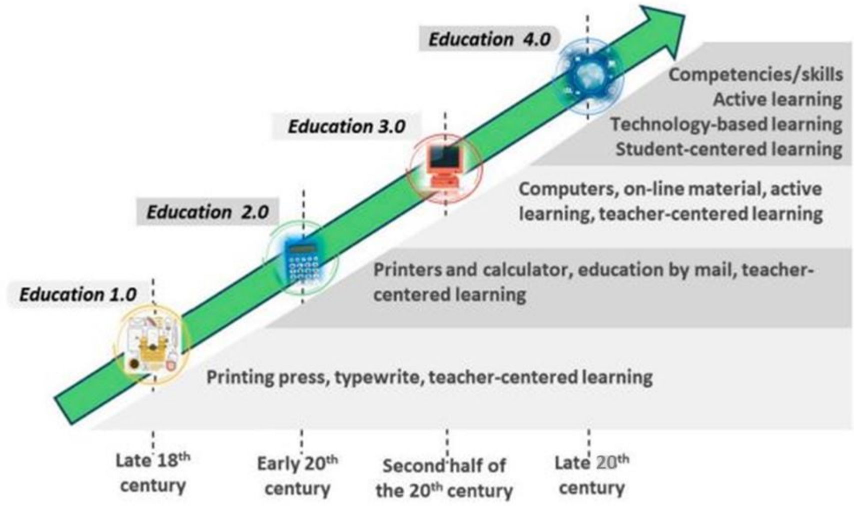

Figure 1. Timeline and key points of educational transformations (De Souza, A.S.C. and Debs, L. 2024).

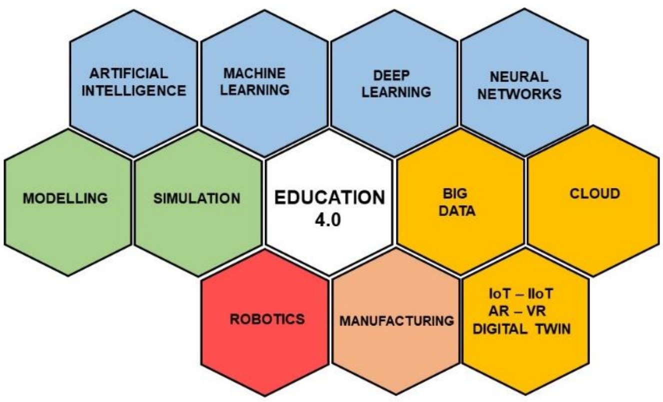

Figure 2. Components of Education 4.0 identified by Industry 4.0 requirements (adapted from Chakraborty S., et al., 2023).

22 – An outline plan for updating the content of chemical and process engineering courses

The various frameworks of Education 4.0 components in the service of Industry 4.0 show the complexity of declining a reasonable update in the already busy curriculum of chemical and process engineering education. The integration of new digital technologies requires the development of new skills or the enhancement of existing ones. It is difficult for chemical and process engineers to master all digital technologies, in addition to the basic knowledge specific to their field. Similarly, digital specialists cannot, for example, be experts in chemical engineering unit operations. We therefore need to create the conditions that will enable both communities to work together and provide each with the minimum knowledge required for efficient interaction.

A first immediate recommendation is to share the currently disjointed languages between the chemical and process engineering community and that of artificial intelligence and digitization experts, in terms of mutual understanding. Zandi, M. et al. (2022) have published the results of an international survey coordinated by IChemE concerning, among other things, the inventory of languages, codes, and software examined. The question submitted to the university community was: What computational software digitalization technologies are covered or taught in your programs? The one concerning the world of industries was: What computational software should future chemical and process graduates know of? Table 1 presents a limited extract of the most frequent answers.

Table 1. Industrial requirements and effective teaching in terms of digitized language, code, and software.

Population	Microsoft Excel	Matlab	Python	Aspen Plus	PSE gPROMS	Hysys
Industry (%)	97.6	65.9	75.6	46.7	31.7	22
University (%)	92.5	94	50.7	68.7	20.9	53.7

Industrial demand for the Python programming language is particularly strong.

To design an applicable and acceptable framework, it is then necessary to assess the quantitative weight of each of the competency markers identified in Figure 2. Using Blum's taxonomy, Carretero, G.S. et al., (2017), Zandi, M. et al., (2022), Udugama, I.A. et al., (2022) and Vuorikari, R., (2022) have, based on expert opinions, respectively specified the relative relevance of each skill family. First of all, consider that the skills "Modelling" and "Simulation" already correspond to areas included in the chemical and process engineering curriculum, with a maximum level of requirement, i.e. "create" on the Blum scale. The overall trend from the synthesis of the results examined shows that the fields of digitalization and big data would be the most relevant concepts to introduce in the curriculum. In quantitative terms, Table 2 provides an estimate of the Blum scale for data science and big data skills.

Table 2. Example of a Blum scale assessment of "data literacy" skills (Zandi, M. et al., 2022).

Blum scale	Remembering	Understanding	Applying	Analysing	Evaluating	Creating
Data science (%)	21.9	29.3	9.7	12.2	2 .4	4.9

Buyel, J., (2024) proposed an interesting detailed schematic representation of data literacy skills and competencies illustrated in Figure 3.

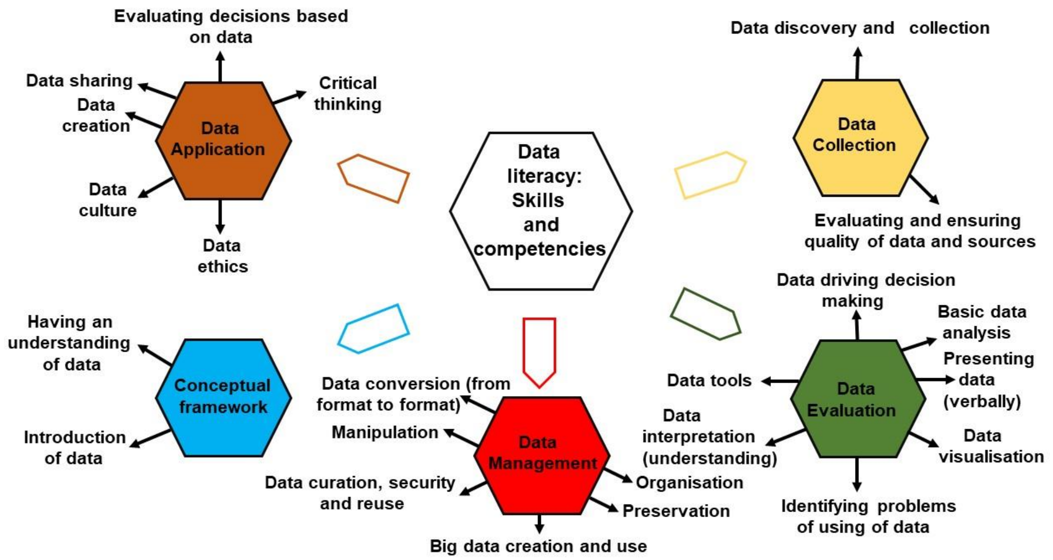

Figure 3. Schematic representation of data literacy skills and competencies (Buyel, J., 2024).

In principle, this presentation means that you can either choose an exhaustive course incorporating all the elements identified in the curriculum to be updated or select only certain optional components for consolidation in the existing curriculum. In reality, however, this is not a trivial matter. One also has to remember that there are many pressures on chemical engineering programs to add additional material on topics such as Life Cycle and Socio-Economic Analyses, Life Sciences, Nanotechnology, Renewable Energy, Advanced Materials and

Additive Manufacturing, Virtual and Augmented Reality, etc.

221 – Literature review

Several experiences of introducing data science methods into chemical and process engineering courses are reported in the literature**.**

Beck, D. A.C., et al. (2016) consider that in terms of data science, the chemical engineer should be able to perform the following tasks: manage a huge data set consisting of ensembles of spatiotemporal data, sensibly read the data in a computationally scalable manner, and extract knowledge from this pile of information with robust techniques whose statistical reliability can be quantified. The authors point out that there may be room for small tweaks in the curriculum to accommodate data science or that an obvious alternate choice would be the addition of elective coursework.

In a report endorsed by the US National Academies of Sciences, Engineering, and Medicine, Kaler, E. W. (2022) examined, among other things, the impact of data science on the evolution of chemical and process engineering training content. The author recommends that data literacy be taught more effectively as a separate course integrated with chemical and process engineering issues.

Feise, H. J. and Schaer, E. (2021) discussed the contents of chemical engineering and biochemical engineering courses (Bachelor and Master levels) recommended by the Process Net network in Germany. The authors consider that the new directions of Education 4.0 to meet the needs of Industry 4.0 do need to be taught, but also point out that available teaching time is already severely constrained. An update of the chemical and process engineering digitization program should result from a compromise on the level of skills, but without compromising the basic knowledge of chemical engineering. This conciliation is the responsibility of the teachers concerned.

A four-part series in Chemical Engineering Progress Magazine (2016) special issue on big data analytics discusses what big data is (White, D. 2016), gives some success stories (Garcia-Munoz, S. 2016), describes how to get started (Colegrove, L.F. 2016) and what the challenges are (Reis, M.S. 2016).

Similarly, a series of articles published in The Chemical Engineer under the auspices of IChemE describes the integration of digitalization in education (Ventura-Medina, E., et al. 2022), (Kilbride, H. and Sinanan, K. 2022) and (Proctor, M. and Chiang, L. 2023).

Bolton, K., et al., (2023) commented on the revision of IChemE's guideline issued in 2021. One of the main types of change concerns the introduction of digital tools and the use of big data analytics.

Using the Process Net program framework as a basis for work, orientation, and discussion in terms of digitization, Stankiewitz, A.I. et al. (2021) compared similar programs at the TU Delft (NL) and Warsaw (A) Universities of Technology. The authors underlined how the new teaching areas have been integrated into the respective curricula, mainly in the form of specialized optional modules, but point out that they are convinced that there is no one-size-fits-all solution.

The synthesis by Duever, T.A., (2019) reports on feedback from the situation in twelve chemical engineering departments in Canada. These authors show that all contain a fundamental probability and statistics course, an introductory computing programming course, a course on engineering computation/numerical methods, and in some a course on advanced statistics, usually experimental design taught as an elective. As mentioned above, the skills required to apply data science methods include data access and management, databases and data warehousing, statistical methods including classification and clustering, time series, various regression methods multivariate statistics, and data visualization. In conclusion, it is unlikely that existing courses are sufficient to cover all the required topics.

222 - Proposed application examples

Following this review of some pedagogical experiences with the introduction of data processing methods in a chemical and process engineering curriculum, it is proposed to summarize the elements of a proposal applicable in the French academic environment. What do we teach with digitalization in chemical and process engineering? Why must chemical and process engineers care about it? What can be done to better prepare graduate chemical and process engineers for the realities of today when it comes to data analysis and AI?

In practice, the challenge of the chemical and process engineer is collecting more data (volume) from different sources (variety), more complex in terms of using the right data and the right tools (analytics) to make the right decisions in real-time (velocity) (Chian, L., et al., 2017). The chemical and process engineer should possess the respective abilities to use and/or develop the Big Data processing architecture, the appropriate mastery of algorithms, the data modelling and to judge the relevance of the validity of the results generated by data analysis (Qin, S.J., 2014).

One option to address this is to adjust the curriculum by modifying existing courses and introducing elective coursework. For example, Commenge, J.M., (2020) has introduced optional AI teaching for process engineering (initiation) into the "Ingénieur des Industries Chimiques (I2C)" syllabus at ENSIC Nancy. Another solution consists of the introduction of a data science minor module, with illustrative chemical engineering AI examples of easy categories according to Venkatasubramamian, V. (2022). In the case of a more comprehensive optional major module, it is recommended to draw on the respective detailed pedagogical experiences of Venkatasubramamian, V. (2022) and Wu, M., et al. (2023).

2221 – Department of Chemical Engineering – Columbia University (USA)

Up-to-date teaching in the chemical engineering department at Columbia University (USA) simultaneously combines the classical symbolic AI with the more recent data-driven numeric AI. Current topics include symbolic knowledge representation, symbolic reasoning and inference, knowledge-based expert systems, modern machine learning methods, hybrid AI models, domain-specific languages, compilers, and knowledge engines. All these are discussed using chemical engineering case studies in process monitoring, diagnosis, control, process/product design, scheduling, optimization, and process safety.

The course content, spread over a 13-week semester with 2 lessons per week, includes the following topics as indicated in Table 3. The detailed topics and the corresponding papers and books cited for each topic are detailed in Venkatasubramamian, V. (2022). The course is completed by a 6-week programming project. The author underlines that building hybrid AI models is more appropriate for many chemical engineering applications. He classifies AI applications into three categories: "easy," "hard," and "harder" problems, and discusses the possible corresponding pedagogical progression.

The author points out that the proposed framework can be used by any teacher to develop his or her teaching program, in whole or in part.

Table 3 – Main topics of the AI course content (adapted Venkatasubramamian, V., 2022).

Topics	Topics
L1 – Introduction to symbolic AI	L8 - Genetic algorithms and directed evolution for materials design
L2 - Python tutorials	L9 - Ensemble learning, boosting, random forest
L3 - Knowledge-based expert systems	L10 - Modelling with deep neural nets and Recurrent neural nets
L4 - Review of linear algebra, probability, and statistics	L11- Reinforcement learning and graphical models
L5 - Clustering techniques	L12 - Hybrid AI models
L6 - Classification techniques	L13 - Domain-specific ontologies, languages, and compilers
L7 - Regression techniques	

2222 – Department of Chemical Engineering – KU Leuven (B)

Wu, M., et al. (2023) introduced in Europa one of the first structural courses about AI applications in process industry 4.0 for the chemical and process engineering curriculum.

The teaching modules aim to provide an understanding of the conceptual knowledge of AI techniques and apply the methodologies learned in process engineering operations. An overview of the course objectives based on Bloom's taxonomy is given in Table 4.

The course was given in eleven lessons, offered once a week, and took 3 h for each class. The lessons cover theoretical parts with frontal lectures and practical parts with hands-on exercises applying active learning methods. The frontal lectures were given in the first six lessons of the course with the following topics: Introduction and general overview - Error, loss functions, and gradient-based optimization - Artificial neural networks, scaling, and feature selection - Heuristic optimization and hybrid modelling - Model predictive control - Data flow and measurements in the chemical industry. The details of the frontal theoretical lectures and practical parts (eleven hands-on exercises) are given and explained in Wu, M., et al. (2023).

This example gives excellent guidelines to other educators in academia and industries for shaping a data science class for chemical and process engineering students.

Table 4 – Overview of the course objectives for factual, conceptual, procedural, and metacognitive knowledge versus Bloom's taxonomy (adapted Wu, M., et al. 2023).

	Remember	Understand	Apply	Analyse	Evaluate	Create
Factual knowledge	**OBJECTIVE 1**	**OBJECTIVE 1**				
Conceptual knowledge	**OBJECTIVE 1**	**OBJECTIVE 1**	**OBJECTIVE 3**	**OBJECTIVE 2**	**OBJECTIVE 4**	
Procedural knowledge	**OBJECTIVE 3**	**OBJECTIVE 2**	**OBJECTIVE 4**	**OBJECTIVE 2**	**OBJECTIVE 5**	**OBJECTIVE 5**
Metacognitive knowledge			**OBJECTIVE 5**	**OBJECTIVE 5**	**OBJECTIVE 4**	**OBJECTIVE 6**

Objective 1: Expect students to understand the theories of ANN, MLP, optimizers, and so on.
Objective 2: Expect students to identify the most suitable technique for the application fields
Objective 3: Expect students to implement the learned concepts in Python
Objective 4: Expect students to critically think about the code application and modification
Objective 5: Expect students to creatively solve chemical engineering problems using the learned concepts
Objective 6: Expect students to independently learn, understand, and apply new concepts of AI

3 – Impact of digitalization on updating the process safety curriculum.

Chemical engineering and process safety are connected interdisciplinary subjects. As such, a comprehensive syllabus in process safety included in a chemical engineering curriculum should cover a wide range of topics, from basic physical and chemical phenomena and unit operations to complex and increasingly automated systems, designed and operated by humans. The global nature of the process industry 4.0 implies a need for standardizing the process safety curriculum. However, the time allocated to process safety varies significantly between universities and study programs, and the competence and experience of the academic staff, including research activities and cooperation with industry, is also likely to influence teaching practices and priorities. Finally, since the process industry in a country or region is likely to reflect its natural resources and the level of technological development, teaching process safety may also vary between academic institutions and study programs in different parts of the world. In this perspective, it is not straightforward to decide which topics to include in a curriculum on process safety, what level of detail to cover, and how the courses should be organized and delivered to maximize learning outcomes and relevance for future employment.

Actually, in France, the first feedback on the impact of the technologies of the industry of the future, in particular those for communication, interconnection, and data management, shows the impact of their potential on the assessment of Security 4.0. The development of various sensors, monitoring instruments, and automated systems has made it possible to collect a wealth of process operating data. The Internet of Things (IoT) and the Industrial Internet of Things (IIoT) have provided the means to connect this data. All this data should be able to be used to improve the production process, risk assessment, Operator Interface 4.0, safety control systems, safety barriers, alarm management systems, early warning signals, corrosion monitoring, remote sensing, increased connectivity, the application of predictive models based on real-time data, and machine learning, etc. In a recent survey on the teaching of process safety, Skold, T., (2024) underlined more generally the implication of the use of AI in risk assessments.

Classical risk analysis and assessment methods and techniques are usually classified into two main segments. The first includes Bayesian networks, dynamic Bayesian networks, fault tree analysis, event tree analysis, and the bow tie. The second includes hazard and operability studies (HAZOP), HAZOP-related expert systems, and the layer of protection analysis (LOPA). Among these tools, the HAZOP method, the tree method, the bow-tie graph, and the LOPA method are traditionally used in the application of good qualitative, semi-quantitative, and quantitative assessment practices (Khan, F., et al. 2015). They apply to a static operating situation and fail to capture the variation in risk that occurs as the process and its environment evolve. They are unable to take into consideration variations in variables, common causes of failure, conditional dependence between events contributing to an accident, or more generally to introduce new information and evidence. In addition, primary events and safety barriers are assumed to be independent of each other. They also consider the relationships between events to be mainly binary and do not take account of dependencies between contributing factors. Nor are they in a position to use information on accident precursors to revise risk profiles. Finally, probabilistic estimates are often still based on data obtained over the years, which can introduce a degree of uncertainty into the analysis. In short, this static approach no longer corresponds to reality. To cope with risks in a changing environment and overcome the limitations of these traditional methods, the inclusion of risk dynamics, in conjunction with recent and accurate information, in these assessment methods is therefore now a necessity to make 4.0 operators and various stakeholders aware of the requirements of process safety 4.0 (Qian, Y. et al., 2023).

Khan, F., et al (2021) presented examples of the integration of digital process safety into the chemical engineering curriculum, to adequately respond to the 4.0 process industry's emphasis on digital solutions. The authors consider that the impact of the increased complexity generated by digitalization is particularly noticeable in four areas: management of abnormal situations, automation and process control, process reliability (software), and process integrity (aging). The corresponding teaching contents are described. Their global or partial implementation is the responsibility of the teachers concerned, in the context of the local process engineering curriculum.

Adopting the "Knowing - Acting and Being" taxonomy in training, Gajek, A., et al., (2022) present a new global proposal for an integrated curriculum for the Safety 4.0 concept, which can respond to the revolution of the 4.0 industry. Depending on the human, material, and financial availability of educational structures, two training approaches can be recommended. The former consists of coupling the current classical process safety education, with one of the specialties responding to the needs of Industry 4.0. The latter, more revolutionary for young people who are already familiar with modern technologies, is to provide integrated teaching of the joint subjects of Safety 4.0 and Industry 4.0.

Laurent, A., and Fabiano, B., (2022) reported critical perspectives concerning the new professional skills in process safety education. Two potential solutions are thus possible either to carry out partial or total retraining of current employees - or to educate new employees hired from the younger and newer generations. The most likely solution would be a hybrid proposition of the two previous possibilities. Examples of applications are reported. It is recommended that appropriate degree courses in chemical engineering and process safety including the study of the new constraint of digitalization 4.0 should be delivered through an integrated approach.

In conclusion, in the new environment of 4.0 technologies, a minimum consideration of system dynamics, in conjunction with the significant emergence of new digital data flows, is necessary and unavoidable in the teaching of process safety within a chemical and process engineering curriculum (Laurent, A., 2023a). Its pedagogical content should be limited to the contribution of simulation, Bayesian networks, and fuzzy logic to the dynamic completeness of classical risk analysis methods. For example, the content of a so-called minor module could consist of two parts. On the one hand, the coupling of the dynamic HAZOP method and the simulation of a styrene polymerization process could be progressively taught in three successive stages of increasing difficulty. Secondly, a comparison of the conventional bow-tie graph method, its Bayesian approach, and its application of fuzzy logic to storage tank safety would complete this advanced initiation module.

4 – Digital tools to support teaching

The 4.0 digital revolution has also generated a variety of digital teaching aids. Feise, H.J. and Schaer, E. (2021) have identified various tools, methods, and platforms that can be used in chemical engineering education. They also highlight the potential contribution of virtual and augmented reality, as well as active simulation through digital games. But they also point out that the digitalization of teaching has not replaced face-to-face teaching. EFCE Working Party Education has prepared a description of active learning tools and/or methodologies such as mind maps, blended learning, flipped classrooms, interactive tools, video capsules, project-based learning, conference training, and online formative tests (EFCE WPE, 2024).

Following a survey of teachers and industrialists in the IChemE community, Udugama, I.A., et al. (2023) have identified which tool can be ideally suited to support teaching a given chemical engineering concept that can be challenging**.** The survey respondents rated Microsoft Excel (VBA), commercial simulators, and scripting tools as ideal for teaching core subjects such as mass and energy balances, mass transfer, and reaction engineering while respondents found 3D Models, and Virtual/Augmented Reality models as being most suited for teaching subjects such as process design, safety and sustainability.

The presentation will be limited to four tools: digital twin (DT), virtual reality (VR), augmented reality (AR) and machine learning (ML)..

41 – Digital twin (DT)
A digital twin is a virtual clone or replica of a physical system or a process. It systematically involves the existence of a pair made up of the digital model and the object that is being copied. The objects involved may be a product, a machine, a production line, a process, or a supply chain. Depending on the concerned system and its desired use, this model may be geometric, metaphysical, functional, or behavioural. It must evolve like its real twin. This twin makes it possible to improve steering, safety, and the optimization of production lines and factories, enhance digital continuity at the product level, from design to end-of-life, and enhance surveillance and predictive maintenance. It makes it possible to put in place new economic models in the supply chain. It makes it possible to increase the quality of products by improving process correction. It allows increased traceability of objects and processes, integrating greater information on the components, suppliers, and production. It is a disruptive tool when it comes to training needs and demonstrations using systems that are complex and hard to duplicate or transport (Laurent, A., 2023b).
Tanner, J. and Nexbery C. (2022) reported that DT is applicable and relevant to all stages of plant life in the chemical and process industries. They underlined that chemical and process engineers at all levels must begin to understand and embrace DT so that they know when, where, and how to apply this key digitalization toll to the best advantage.

411 – DT for the teaching of distillation control
Taube, M.A., et al., (2024) discuss the development of a digital twin-based accessible approach to the education of real-time control of distillation. The hands-on approach is visual and time domain-based, making the conceptual connection between the physical process and the control system design clearer and promoting intuitive learning. An example of a one-day workshop is designed to equip chemical and process engineers with practical insights and skills needed for designing and troubleshooting distillation control equipment. The content of the course delivered in the Department of Chemical and Materials Engineering at Auckland University (NZ) is described in Table 5.

Table 5 – One-day workshop schedule for a DT approach to distillation control (Taube, M.A., et al.,2024)

Time	Description of the content of the course
Session 1	General introduction to the course and its objectives Introduction to distillation process simulation and process dynamics
Session 2	Hands-on exercises in setting up a distillation column in a process simulator, such as Aspen Hysys or SLB symmetry
Session 3	Defining stabilizing and composition controls covering, controller manipulated variable/ controlled variable pairing (MV/CV pairing) methods and practical considerations and constraints
Session 4	Hands-on exercises to evaluate process dynamics, effects of different MV/CV pairings, and running a dynamic distillation control simulation

The approach based on digital twins relies on the use of industrial process simulators to develop digital models. Here the digital twin to the distillation control simulation platform was Aspen Hysys with basic models already developed for use. As a result, the lessons learned from this approach are directly transferable to real-world engineering problems that are found at every operating plant.

412 - Virtual Reality (VR) and Digital Twins (DT) for enhanced learning in chemical engineering
Galeazzi, A., et al., (2023) explored the implementation of immersive virtual reality and digital twin technology to engineering education in the M. Sc. chemical engineering program at Politecnico di Milano (I). A case study involving a valve switch in a process line illustrates the practical application and benefits of digital twins. The process includes isolating the automatic valve by closing adjacent manual valves, opening the bypass valve, and draining the liquid from the isolated section. Interactive training scenario showcasing a valve bypass operation. The central valve is the target of the exercise due to its malfunction. To successfully navigate the tutorial, participants must isolate this valve by adjusting the neighbouring manual isolation valves and initiate flow through the bypass by engaging the manual wheel valve located near at hand. This digital

twin valve switch exercise offers students an immersive VR-based tutorial, enabling them to gain practical experience in simulated plant operations.

413 – DT as a virtual home laboratory for fluid mechanics

Boettcher, K., et al. (2023) presented a laboratory that requires gaining importance, in the medium and long term, for the increasing digital transformation and the changing competence requirements. A newly developed online laboratory experiment in immersive virtual reality is used for teaching chemical and process engineering students at TU Dortmund University (D). For this purpose, a DT of a jet pump was realized using Unreal Engine 4, a development environment for immersive computer games. To better integrate the changing competence demands of Industry 4.0 a real-world scenario (RWS) to address the sometimes-vague problem-solving assignments has been designed to simulate work-integrated learning in R&D on technical equipment of the real Industry 4.0. The development of the RWS was reflected upon through a special checklist, that integrates the fundamental laboratory learning objectives. In this type of practice-related role-play, the students find themselves in an ambiguous situation that they must be cleared and resolved constructively and autonomously. All stages of the teaching support procedure are detailed: DT technical design, RWS instructional design, analysis and coordination checklist of intended learning outcomes, teaching-learning activities, assessment tasks, and evaluation methodology with results.

414 – DT for the decarbonization of the French chemical industry

To propose an adapted and innovative training program for the decarbonization of the chemical industry, a consortium bringing together France-Chimie, the Gay-Lussac Federation (representing 20 engineering schools in Chemistry and Process Engineering) and the ADIUT (in partnership with 19 IUT departments of Chemistry and Chemical Engineering & Process Engineering) is launching the "DécarboChim" project, whose goal is to develop the skills needed to transition the chemical industry to a low-carbon future, in creating new training modules, developing pedagogical infrastructures, and disseminating the culture of decarbonization.

In this context, digital twins are being developed by the different training centers and shared to promote the acculturation of learners with the various techniques and methods of decarbonization of the chemical industry, including technological adaptations (process intensification, flow chemistry technologies), transfer activations (microwaves, ultrasound, photochemistry, catalysis), new design methods (life cycle analysis, energy integration of processes, decarbonization strategies, Greenhouse Gas (GHG) balances, CO_2 capture processes, batch-continuous transposition), new production methods (digitalization, optimization of production), use of new raw materials (recycled & bio-sourced materials) and uses of new energy sources (electrification of processes, use of alternative energies, storage, and energy conversion).

Figure 4 gives an example of the first digital twin operated in VR, developed at ENSIC Nancy as a part of this project (https://u2l.fr/vr360-ensic-2). Learners can thus visualize the different equipment of a practical work installation for CO_2 capture by amines and visualize the transfer phenomena occurring inside the absorption column.

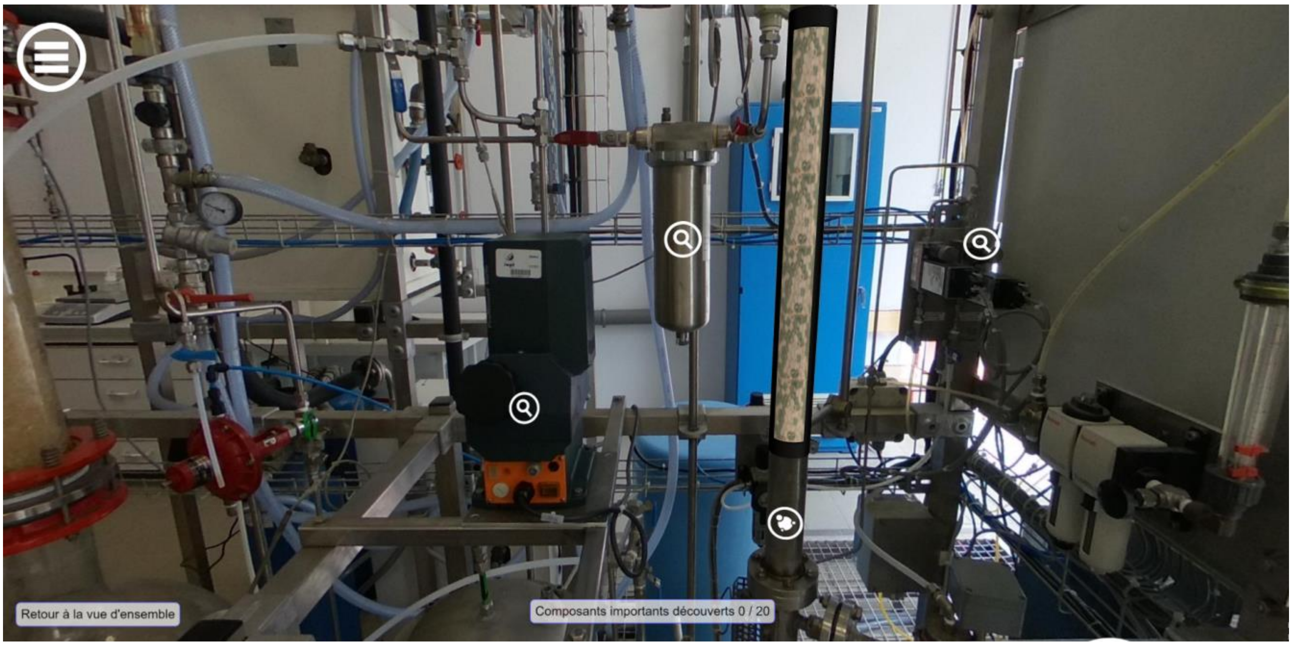

Figure 4. VR view of a practical work applied to the capture of CO_2 by amines.

Ultimately, they will be able to complete the practical work in VR, regardless of their training location, and thus better train themselves on the different technologies making it possible to contribute to the decarbonization of the industry.

415 – VR –AR explored in the European "*CHARMING*" project

Recent developments in immersive learning technologies are providing exciting new tools for teaching and training programs, yet they remain underutilized in science & technology education, and nowhere is this more real than in the field of chemistry and chemical engineering. *CHARMING*, the European Network for Chemical Engineering Immersive Learning, takes on this challenge by developing learning strategies, content, and prototypes for the application of games and virtual/augmented reality (VR/AR) for motivating, teaching, and training children, students, and employees in chemistry, chemical engineering, and chemical operations. The inter-sectorial and interdisciplinary *CHARMING ETN* consists of leading universities and industry participants and trains 15 Early Stage Researchers (ESR) in the areas of innovative chemical engineering, instructional psychology and pedagogy, and immersive technology. *CHARMING's* success is based on integrating these three areas to provide Europe with highly trained young experts who are ready to help motivate, train, and integrate the next-generation human capital of the European chemical industry and beyond.

The detailed *CHARMING* project, with team, partners, events, communications, repository, and videos is described in *CHARMING* (2024).

By way of examples, various video clips are available, such as:

- Operate your own reactor: a VR training for the chemical industry.
- AR laboratory prototype for chemical engineering education.
- VR for safety training in chemical laboratories.

Similarly, Solmaz, S. and Van Gerven, T., (2022) have proposed a generic system architecture and examined methodologies for integrating CFD simulations with AR/VR. The results indicate that system architecture has a promising usefulness in prescribing a development strategy. The study provided a generic design model and various workflows for developing educational tools with CFD and AR/VR.

Fracaro, S.G., et al., (2021) reported research being conducted to develop a virtual reality training solution as part of the *CHARMING* project. The paper includes the design principles for a virtual reality training environment including the features that enhance the effectiveness of virtual reality training such as game-based learning elements, learning analytics, and assessment methods. The VR working prototype will be implemented to provide conclusions regarding the effectiveness and efficiency of the VR training experience compared to traditional classroom training as well as digital-based platform training in the chemical industry.

Fracaro, S.G., et al., (2024) assessed the self-perception of the participants on safety readiness when exposed to emergencies in virtual reality, and evaluated if the responses would differ if different emergencies were presented to the participants. It should be considered that VR is a tool to help the operators train and learn the procedures that are impossible to train in real life.

42 – Machine learning

Artificial Intelligence (AI) and Machine Learning (ML) have recently gained increasing interest among chemical and process engineers. AI can be defined as a set of methods enabling to reproduction of human behaviour to solve high-complexity problems, such as speech recognition, linguistic translation, and image analysis. ML is a subset of AI, referring to a set of algorithms whose performance, relative to a given task, improves upon receiving more and more relevant data (i.e., the computer program is considered to be learning from experience). Given the dataset, the user will provide to the algorithm, the latter will identify on its own, without being explicitly programmed by the user, eventual mathematical correlations and patterns among them. This current great popularity of ML is mostly driven by the increasingly facilitated access to large amounts of data of diverse varieties along with the major advances in modern computational systems that are becoming more powerful and affordable every day (Trinh, C., et al., 2021).

It is proposed to illustrate the use of ML in a chemical engineering curriculum. Hands-on activities have always accompanied chemical engineering courses since it is necessary to talk about theoretical knowledge and hands-on capability to solve practical problems.

421- ML in the Department of Chemical Engineering at the University of Sao Polo (Brazil)

Lavor, V., et al., (2024) discuss the design and implementation of a hands-on learning framework developed in the Department of Chemical Engineering at the University of Sao Polo (Brazil), for a course in chemical engineering. The hands-on activities covered basic concepts of unsupervised learning, clustering, several techniques in supervised learning, classification, and regression. The activities also included the study of Artificial Neural Networks (ANN), a powerful tool for modelling complex relationships in data. The Colab tool was used for the development of hands-on activities and validated its effectiveness in training students to be confident and self-directed learners.

The learning objectives for the hands-on activities are specifically: - Recognize ML basic concepts; - Use the Colab tool to develop the ML basic concepts; - Analyse the datasets; - Carry out clustering by implementing different techniques; - Executing classification using decision tree and SVM; - Implement linear and multilinear regressions; - Generate ANN using Keras.

The content of the syllabus, with a workload of 60 hours, is:

- A presentation of the course; an introduction to Scilab; Tutorial of Scilab.
- Linear Systems of Algebraic Equations. Sparse matrix.
- Qualitative method for solving ODE. Critical points: nodes, saddle, center, spiral points. Geometric analysis of linear systems.
- Almost linear systems. Phase plane. Phase portrait. Classic dynamic systems: chemical reacting, pendulum, and population balances.
- Numerical Methods for Non-linear ODEs with Initial Conditions. Euler, Runge-Kutta, multistep, and BDF methods.
- Numerical Methods for PDE. Finite differences. Fictitious domain method. 2D heat diffusion.
- Introduction to Artificial Intelligence: search, learning, reasoning.
- Machine Learning: clustering, classification, and regression. Datasets are available on the Internet. Ranking metrics. Logistic function.
- Deep Learning: Artificial Neuronal Networks (ANN).
- Stochastic processes: Brownian movement, Wiener process, stochastic differential equations. Applications using Python library.

The main topics within ML covered in the classroom and transformed into tasks to be developed by students are meticulously detailed in Lavor, V., et al., (2024). For example, a real industrial milling process, composed of grinding and a cyclone separator, was utilized with a data-driven modelling approach with particular emphasis placed on ANN.

422 – ML in the Department of Chemical Engineering, University of the Philippines (Philippine)

Pilario, K., E., (2024) recently presented an original algorithmic approach for a graduate-level ML course particularly designed such that students will be able to apply ML in chemical engineering. To achieve this, the course intends to cover a wide selection of ML models with emphasis on their motivations, derivations, and training algorithms, followed by their applications to chemical engineering-related data sets. The proposed course consists of 2 meetings per week at 1.5 hours per meeting. The first meeting consists of lectures and class discussions, while the second meeting is dedicated to case studies where live coding sessions in Python are done. Table 6 shows some of the case studies used in class for every module. All the detailed references of each case study are cited in the original paper of Pilario, K., E., (2024). Table 6 highlights the fact that chemical engineers can use ML algorithms on a wide coverage of applications, from process data analytics to chemometrics, materials informatics, energy systems, environmental systems, bioprocesses, and business analytics. Note that the class materials are available to interested teachers through the link: https://github.com/kspilario/MLxChE

Table 6 – List of the modules and associated case studies (adapted Pilario, K., E., 2024).

Module	Case studies
Exploratory data analysis	-Cranfield multiphase flow facility -Taylor Swift's Spotify dataset -Titanic data set -Fisher iris data set
Linear and logistic regression	-Hypothetical metal-organic framework CO2 isotherm data -Flow regime classification using gas-liquid velocities
Support Vector Machine (SVM) Kernel ridge regression	-Fault classification in an evaporator -System predicting energy efficiency in buildings
Hyperparameter tuning	-Wine quality data set -Air quality data set
Gaussian process regression Bayesian optimization	-Airline passenger's data set -Battery degradation data set -Microalgae moisture content data during drying -Atmospheric CO2 data at Mauna Loa
Neural network Recurrent Neural network	-Chlorophyll-a in global lakes data set -Identification of an evaporator system -Global solar irradiance and wind speed forecasting
Naïve Bayes – decision trees Random forest	-Diamonds Data Set -Gas turbine CO and NOX emissions data -QSAR-based pesticide aquatic toxicity data
Principal Component Analysis (PCA)	-Hypothetical MOF database -Chemometric data on bee substance
Stochastic Neighbourhood Embedding (SNE) t-SNE – Laplacian on eigenmaps	-Flow regime mapping using pressure signal Feat -8 × 8 Handwritten digits recognition
K mean clustering – Gaussian mixture models Spectral clustering	-Anomaly detection in a wastewater treatment plant -Tennessee Eastman Plant

5- Conclusion

In conclusion, the evolving landscape of Industry 4.0 acts as a catalyst for innovation in education: It is imperative to maintain a strong foundation in the fundamental principles of chemical and process engineering. While integrating advanced digital tools and AI technologies into the curriculum is necessary to prepare students for the demands of modern industries, this should not come at the expense of the core knowledge that has traditionally underpinned the field. The examples and frameworks provided in this discussion serve as guidelines for educators seeking to modernize their teaching approaches. They emphasize the importance of incorporating hybrid AI models, which combine the strengths of symbolic and data-driven AI, as these have proven particularly effective in addressing the complex challenges inherent in chemical and process engineering.

However, it is crucial to recognize that there is no one-size-fits-all solution. Each educator must adapt these recommendations to fit the specific context of their university, the industrial needs of their region, and the economic, ecological, and technological environments in which they operate. The diversity of teaching contexts means that some may fully embrace these new methodologies, while others may choose to integrate only selected components into their existing curriculum. Ultimately, the decision on how best to prepare the next generation of engineers, rests with the individual educator, who must consider the available resources, the specific skill sets of their faculty, and the evolving demands of the industry.

The flexibility in adopting these educational innovations ensures that chemical and process engineering education can remain both rigorous and relevant, equipping students with the skills they need to thrive in an increasingly digital and interconnected world, while also preserving the essential knowledge base that defines the discipline.

The identified challenges and concerns revolve around generative AI tools, such as ChatGPT and Copilot, and deal with:

- Loss of engagement: If AI can provide the answer, why bother learning or understanding the underlying concepts? This echoes the "Wikipedia effect" from 15 years ago (why learn when everything is available online?), but at a much deeper level, as the concern now shifts from knowledge to technical skills,
- Deflection of responsibility: A tendency to say, "the AI said so," as a way to avoid accountability,
- Complacency: While one could complete a task independently, the convenience of AI leads to delegating it. Over time, this reliance on machines may erode individual expertise,
- Data protection and dissemination: A growing number of companies are prohibiting their engineers from using generative AI due to data security concerns, opting instead to develop their own internal GPT-like models,
- Fear of dehumanization: A worry that the increasing use of these tools diminishes the human element in processes,
- Standardization of responses: Concerns that the outputs generated by AI lack diversity and originality.

These concerns underline the importance of carefully assessing the integration of such tools in professional environments.

The digital revolution has also a pivotal role to play in continuous education and lifelong learning, as detailed Meyer, Th et al. (2022). The advent of advanced digital tools, online platforms, and e-learning resources has transformed how professionals access and engage with training. These technologies enable flexible, personalized learning experiences, that can be tailored to the specific needs of engineers, allowing them to stay abreast of the latest developments in their field and remain at the forefront of industry advancements, driving efficiency, sustainability, and innovation in process engineering.

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