

## Evaluate the drivers for digital transformation in higher education institutions in the era of industry 4.0 based on decision-making method



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### ABSTRACT

The digitalization of higher education (HE) institutions and relevant issues have attracted the attention of many educational stakeholders. ICT has become a subject of high importance in every context, particularly in the workplace; thus, a principal goal for universities and schools is to prepare future professionals capable of dealing with problems and searching for effective solutions by their digital competence as a key skill. In this regard, a new framework is developed to evaluate the main drivers of digital transformation in higher education institutions (HEIs) in the era of industry 4.0. The developed framework is proposed a decision approach that can effectively use the presented information to make decisions of high rationality. This framework is applied to compute the subjective and objective criteria weights, and it is used to assess the preferences of organizations. An empirical case study to evaluate the main drivers for the implementation of digital transformation in HEIs is taken. According to the findings, the most significant drivers for the implementation of digital transformation in HEIs in the era of Industry 4.0 are developing, updating, and adapting a curriculum (0.0425), integration of digital technologies for universal education (0.0420), and cloud computing (0.0419), respectively. Hence, the evaluation results also show that the option higher education institution (HEI)-4 has the highest overall utility degree (1.845) over different drivers for the implementation of digital transformation in HEIs in the era of Industry 4.0. Also, comparison and sensitivity investigation are made to show the superiority of the developed framework.

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### Introduction

In recent years, higher education institutions (HEIs) have been flooded by many technological advancements mostly induced by the Industrial Revolution 4.0; this situation has forced HEIs to deal with a digital transformation in all dimensions (Benavides et al., 2020). Therefore, numerous researchers have attempted to investigate the best way to apply the digital transformation approaches to HEIs and, this way, to shed light on the complicated relationships between different actors playing roles within an education domain supported by state-of-the-art technologies. The development of ICT skills development is known as vital to the complete and active societal participation of students in the future (OECD, 2015a, 2015b); on the other hand, the use of digital media in teaching and learning cannot necessarily guarantee their active engagement (Kirkwood, 2009) or high

achievement (Tamim et al., 2011). Note that change does not occur simply by being only in contact with new technologies (García et al., 2015); rather, it is important for teachers to have pedagogical competence in the use of educational technology (Englund et al., 2017; Javed et al., 2022; Kirkwood & Price, 2005; Ng, 2012) and also to model acceptable digital citizenship (Choi et al., 2018). Academic findings have revealed that novice teachers are more adaptable to rapid changes and developments in comparison with more experienced ones (Englund et al., 2017). The experienced teacher has indicated that the lack of digital skills prevents them from implementing educational technologies in their classrooms; another problem stated them is systemic problems, for instance, inaccessibility of technology and workload (Jääskelä et al., 2017; Majid et al., 2022; Marcelo & Yot-Domínguez, 2019; Margaryan et al., 2011). Recently, a survey was conducted on the UK digital education organization Jisc, with over 22,000 students from 74 UK and 10 international organizations. The findings revealed that the full benefits of technology in learning contexts had not been realized yet, and technology is more commonly

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implemented in these contexts for convenience rather than for pedagogy effectiveness (Newman & Beetham, 2017).

Innovations created by educational technologists often are not adopted despite many effective educational technology innovations (Archer et al., 2014; Tatar et al., 2008) and an increasing willingness of educational institutions the implementation of technology (Cheung & Slavin, 2013). As predicted by the diffusion of innovation theory, the innovation adoption rate could be increased if teachers perceive that innovations are capable of solving their challenges (Rogers et al., 2014). Educational technologists desire that their proposed technologies be used long-term or well-integrated into educational processes (de Koster et al., 2017). To this end, the diffusion of innovations literature urges the need for understanding the challenges perceived by teachers in classroom practices, designing effective technologies helpful in coping with such challenges, and communicating these benefits (Zaritsky et al., 2003). It is important for educational technologists to make a balance among the requirements of multiple stakeholders (Easterday et al., 2018), especially those who are responsible for adopting technology in a classroom. As a result, a good starting point for encouraging the use of educational innovations is an empirical framework that describes the teachers' perceived challenges in this context.

At present, the technological adoption of universities is connected to a paradigm shift, where technology is regarded as a complicated and interconnected environment that allows digital learning (Mahlow & Hediger, 2019). Additionally, the interest is concentrated more upon learners than the technology itself and the learning experiences it brings into the classroom. Digitalization refers not only to the transformation of not just work environments but all facets of society. More specifically, regarding the educational context, transformation occurs with or without strategic initiatives ensuring the ongoing quality of teaching/learning environments. The education field is essentially reactive, as novel disruptive technologies are developed in other industries and then applied to current educational cultures and systems.

In the recent decade, digital transformation (DT) has been recognized as a priority for higher education institutions (HEIs); this process is necessary for all the organizations claiming to be change leaders and competitive in their relevant domains (Abad-Segura et al., 2020; Alhubaishy & Aljuhani, 2021; Rof et al., 2022). Therefore, several researchers have focused on the definition of DT in business (Ballestar et al., 2021; Ha & Thanh, 2022; Heredia et al., 2022; Skare & Riberio Soriano, 2021; Windasari et al., 2022). For instance, Matt et al. (2016) asserted that DT is concerned with the changes brought by DTs in a firm's business model, which can lead to product modifications, organizational structure, or the automation of processes. After that, Gobble (2018) defined DT as "the profound transformation of business activities and organizations, processes, competencies and models, for the maximum transformation of the changes and opportunities of a technology mix and its accelerated impact on society, in a strategic and prioritized way".

To persist in time, HEIs require evolving in an integral manner. Additionally, two challenging tasks are to effectively exploit all the changes provided by the wealth of DTs and redefine the entire business models across the whole value chain. Such drivers are more persistent in the case of those organizations that are enduringly attempting to make sure of their competitive positions in the international market. Note that a similar concern is arising for universities as they get increasingly involved in the competition for the selection of the best researchers and students (Faria & Nóvoa, 2017). However, numerous universities attempt to develop definite digital strategies to be well adapted to the substantial changes in the use of new technologies; these institutions still lack the capability, vision, or commitment for the effective implementation of these technologies (McCusker & Babington, 2015). In this regard, there is a need to gain an inclusive vision of the whole DT in HEIs in a way to achieve an

overview of the current state of DT in these institutions. It is also important to identify the distinctive features of DT, such as actors, dimensions, and implementations when it occurs in an HEI. Remember that DT in HEIs has been investigated from various points of view and the literature still lacks a consensus on its definition.

The world faces increasing the "wicked challenges", which necessitates preparing adequate university graduates with a range of collaborative and interdisciplinary skills (Oliver & Jorre de St Jorre, 2018). In this sense, many scholars have stressed the high significance of ICT skills and the digitalization of HEIs; Many national, international, and European policies have acknowledged "the need to equip all citizens with the necessary competencies to use digital technologies critically and creatively" (European Joint Research & Redecker, 2017). Furthermore, many findings have revealed that there is an association between higher levels of ICT skills and higher levels of wages (Falck et al., 2021) and on the other side, there is the risk of job loss in the future because of the growth of computerization and automation (Bond et al., 2018). As a result, HEIs need to adopt effective digitalization strategies that could support various 21st-century skills in a way to enable students to implement technology flexibly, innovatively, and adaptively (Oliver & Jorre de St Jorre, 2018).

The studies discussed above indicated that DT needs to be established based on the axioms of connectivism in order to satisfy what different interest groups generally expect in the social, economic, and environmental aspects (Shrivastava, 2018). HEIs will invest in implementing and growing clean technologies in their activities and manage the dissemination of such technologies (Formánková et al., 2018). Clean technology (which is also called environmental technology, green technology, or environmentally-sound technology) refers to those technologies that attempt to decrease the adverse impacts on the environment by some enhancements to energy efficiency, sustainably utilizing the available resources, or taking action in some activities to protect the environment. They produce lower amounts of pollution, use the existing resources more sustainably, and recycle/handle more waste. Similarly, clean technologies could be developed based on the evolution of information and communication technologies (ICT). HEIs are increasingly accepting telecommunications services that are typically hosted online in the cloud; this way, they remove additional physical devices and hardware (Babbitt, 2018). This paper aims to investigate the trends in the DT of HE to analyze the impacts of implementing new technologies by HEIs. Thus, we have developed a new approach to the MCDM method in this study. Further, we aim to conduct a survey study to identify the main drivers for implementing DT in HEIs in the era of Industry 4.0. Therefore, the main objectives of this paper are provided below:

- To recognize the drivers of DT in HEIs using a survey method based on the current literature review and interviews with experts.
- To propose a comprehensive approach to evaluate the main drivers for the implementation of DT in HEIs.
- To introduce the new framework to identify and evaluate the related drivers of DT implementation in HEIs.
- The developed framework is utilized to evaluate and rank the main drivers for the implementation of DT in HEIs in the era of Industry 4.0.

The remaining paper is organized in the following sections. Section 2 discussed the main drivers of digitalization in higher education. Section 3 provides the introduced q-ROF-MEREC-SWARA-CoCoSo method. Section 4 presents the results of the study, the case study, the sensitivity analysis, and the comparison. Finally, section 5 discusses the conclusion of the study.

## Digitalization drivers in higher education

In recent decades, universities have experienced considerable changes due to the social/technological trends toward digitalization. Like all revolutions, DT has intensely readjusted all societal sectors (Abad-Segura et al., 2020). Accordingly, digitalization is a key factor in HEIs, which can attract students and improve their experiences with academic courses, teaching/learning materials, and training procedures in general (Gurung & Rutledge, 2014). Digitalization in HEIs helps to monitor the training hindrances easily and decreases the risk in the university. On the other hand, the literature shows that many HEIs managers are still reluctant to comprehend well and use the opportunities to adopt such a digital environment. Oliveira and de Souza (2021) assert that DT involves changes to the organization of work, which are principally induced by developing digital technologies and innovations in business models. DT essentially refers to something more than the use of a technological solution; rather, it can be recognized as an alignment among three factors, i.e., digital technologies, human beings, and organizational factors. Mahlow and Hediger (2019) believe that DT brings about novel skills and models by means of digital technologies in a strategic and deep way. Education 4.0 plays a leading role in the emerging educational paradigm by applying relevant skills based on the requirement for improving and requalifying, unlearning, and relearning (Hong & Ma, 2020).

DT was defined by Grab et al. (2019) as an element disruptor that causes fundamental changes to entire industries and organizations. According to Bresinsky and von Reusner (2018), digitized organizations must be well-focused on social and technology domains to have a successful transformation. Furthermore, some other scholars (Bygstad et al., 2022; Kuhn & Lucke, 2021; Núñez-Canal et al., 2022; Pham et al., 2021; Sanz et al., 2017; Welsh et al., 2016) consider that DT in HEIs from a renewal business prototype viewpoint are allied with technological trends. Moreover, Rodrigues (2017) identified important elements that are generally intricate in the DT process, e.g., people, strategies, structures, processes, and competitive dynamics. In another research, Sullivan and Staib (2018) and Kaminskyi et al. (2018) considered a social aspect intervening in the DT processes and investigated how DT can improve or replace conventional services/products. Furthermore, Faria and Nóvoa (2017) described DT as a phenomenon that created additional and differentiated value and extended the domain of DT in HEIs to the interactions between a firm and its customers, suppliers, and competitors. In another research, Elena (2017) inspected DT from the education perspective and studied how to integrate digital technologies with teaching, learning, and organizational practices.

The pedagogical forms range is experiencing a substantial expansion, including the illustrations, videos, or presentation materials, the direct link to different databases and information networks, and the chance to get integrated into network communities (Petrova & Bondareva, 2019). Recently, numerous researchers have focused on the digitalization of education with the use of virtual reality (VR) technologies. After the study of Williams (2002) was published, the challenges in relation to access intensified because any technological growth needs Internet connections of higher speed and stability. E. McGovern examined the role of digitalization in forming the students' soft skills, for instance, participation in public speaking sessions, business negotiations, and communication, as well as preparing presentations. According to Williams et al. (2002), the notion of participation refers to the challenge of the achievement of complete participation of both instructors and students in learning environments improved by technology. Moreover, VR technologies help learners to self-assess their own skills, check the direction of their progress, and adapt to the available training programs (McGovern et al., 2020).

Pensel and Hofhues (2017) called for learning/educational environments improved by new digital technologies based on those

theories that give a central role to the learner instead of the teacher. This could be applied to both formal and informal learning environments, as only concrete actions can build relationships between the self and the external world. Boelens et al. (2017) summarized the challenges that may arise in blended learning settings in four areas. At first glance, these four areas seem primarily pedagogical; however, the technology and access issues are indirectly understood as part of all challenge areas. After that, in complementing research, Detyana and Kadiri (2020) showed the benefits of applying VR technologies, for example, higher motivation and engagement of learners. Basically, based on the studies reviewed above, the challenges that have arisen in the area of technology (which have caused the improvement of education with digital, online, and e-learning formats) are either pedagogical or technological. However, according to the above discussion, this study used the current literature review to identify the important drivers of digitalization implementation in higher education. The identified drivers are innovation approaches; augmented reality; digital technologies design; technological resource management; computational thinking; development education 4.0 strategy; 5G networks; creative problem solving; adaptability; creativity; digital games; using innovative pedagogical approaches; social networks; critical thinking and analytical thinking; teamwork; integration of digital technologies for universal education; artificial intelligence; improving the educational experience; using digital technologies using innovative assessment methods; cloud computing; develop, update and adapt curriculum and using digital technologies for educational communication software.

## Proposed q-ROF-MEREC-SWARA-CoCoSo method

Though, in MCDM, some cases may occur in which the decision experts (DEs) may give the value to which an option  $S_j$  holds the attribute  $T_j$  is 0.6, and the value to which an option  $S_i$  nullifies the attribute is 0.9. However, PFS and IFS cannot address such conditions since  $0.6 + 0.9 > 1$  and  $0.6^2 + 0.9^2 > 1$ . To compensate for this inefficiency, Yager (2017) suggested the idea of q-rung orthopair fuzzy sets (q-ROFSs), also depicted by BD and ND. q-ROFSs fulfill a constraint that the sum of the  $q^{\text{th}}$  power of BD and ND are less than or equal to 1, where  $q \geq 1$ . Thus, q-ROFS is a tool of higher flexibility and applicability in handling higher levels of uncertain information. In recent years, many researchers have focused on the q-ROFSs environment. Mishra and Rani (2021) suggested an additive ratio assessment (ARAS) model to solve the problem of sustainable recycling partner (SRP) selection problem.

DEs, in an MCDM process, normally place a high significance on the criteria weights that are described in the literature as *objective and subjective weights*. Kersulienė et al. (2010) proposed the Stepwise Weight Assessment Ratio Analysis (SWARA) approach to compute the subjective weights. Compared to different tools, such as the analytic hierarchy process (AHP), SWARA offers simpler computational processes. In contrast to AHP, there is no need for many pairwise comparisons in SWARA, and SWARA is more consistent. Rani et al. (2020) utilized the ARAS framework to assess the methods previously suggested for treating healthcare wastes on PFSs. In recent years, an innovative MCDM approach, called combined compromise solution (CoCoSo), was proposed by Yazdani et al. (2019), which combined the compromised algorithm with various procedures to obtain a compromise solution. Recently, Liu et al. (2021) made some assessments and selections of the best medical waste treatment method with the help of the Pythagorean fuzzy CoCoSo approach. This section briefly presents the developed method on q-ROFSs as follows:

Consider  $\Xi = \{z_1, z_2, \dots, z_n\}$  be a finite discourse set. A q-ROFS 'M' in  $\Xi$  is defined (Yager, 2017) as  $M = \{(z_i, \mu_M(z_i), \nu_M(z_i)) \mid z_i \in \Xi\}$ , where  $\mu_M(z_i) \in [0, 1]$  and  $\nu_M(z_i) \in [0, 1]$  signify the BD and NBD of  $z_i \in \Xi$ , respectively, with  $0 \leq (\mu_M(z_i))^q + (\nu_M(z_i))^q \leq 1$ , and  $q \geq 1$ . The

indeterminacy degree is defined as  $\pi_M(z_i) = \sqrt[q]{1 - (\mu_M(z_i))^q - (\nu_M(z_i))^q}$ ,  $\forall z_i \in \Xi$ . Also, the q-ROF number is denoted by  $\varphi = (\mu_\varphi, \nu_\varphi)$ . To discriminate the various q-ROFNs, the score and accuracy values are defined as (Liu & Wang, 2018)

$$\mathbb{S}(\varphi) = \frac{1}{2} (\mu_\varphi^q - \nu_\varphi^q + 1), \mathbb{h}(\varphi) = \mu_\varphi^q + \nu_\varphi^q. \tag{1}$$

For any two q-ROFNs  $\varphi_1 = (\mu_{\varphi_1}, \nu_{\varphi_1})$  and  $\varphi_2 = (\mu_{\varphi_2}, \nu_{\varphi_2})$ ,

lowerRoman(%1)

If  $\mathbb{S}(\varphi_1) > \mathbb{S}(\varphi_2)$ , then  $\varphi_1 > \varphi_2$ ,

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If  $\mathbb{S}(\varphi_1) = \mathbb{S}(\varphi_2)$ , then

(a) if  $\mathbb{h}(\varphi_1) > \mathbb{h}(\varphi_2)$ , then  $\varphi_1 > \varphi_2$ ,

(b) if  $\mathbb{h}(\varphi_1) = \mathbb{h}(\varphi_2)$ , then  $\varphi_1 = \varphi_2$ .

Next, the procedure of the proposed q-ROF-MEREC-SWARA-CoCoSo method is given by

Step 1: Make a linguistic decision matrix (LDM)

A set of  $\ell$  "decision experts (DEs)"  $A = \{A_1, A_2, \dots, A_\ell\}$  assess the  $m$  choices  $I = \{HEI_1, HEI_2, \dots, HEI_m\}$  over  $n$  criteria  $D = \{d_1, d_2, \dots, d_n\}$ . Assume that  $Z^{(k)} = (\xi_{ij}^{(k)})_{m \times n}$ ,  $i = 1, 2, \dots, m$ ,  $j = 1, 2, \dots, n$  be the suggested LDM by DEs, where  $\xi_{ij}^{(k)}$  state the ratings of an option  $HEI_i$  over a criterion  $d_j$  in the form of linguistic values (LVs) given by  $k^{\text{th}}$  expert.

Step 2: Computation of the expert weight

To obtain the DEs' weights, the importance ratings of the DEs are provided as LVs and then expressed by q-ROFNs. Let  $A_k = (\mu_k, \nu_k)$  be the q-ROFN, and then the weight is estimated by

$$\varpi_k = \frac{(\mu_k^q + \pi_k^q \times (\frac{\mu_k^q}{\mu_k^q + \nu_k^q}))}{\sum_{k=1}^{\ell} (\mu_k^q + \pi_k^q \times (\frac{\mu_k^q}{\mu_k^q + \nu_k^q})}), k = 1(1)\ell. \tag{2}$$

Here,  $\varpi_k \geq 0$  and  $\sum_k = 1^\ell \varpi_k = 1$ .

Step 3: Create the aggregated-q-ROF-DM

To create the A-q-ROF-DM, a q-ROF-weighted averaging (q-ROFWA) operator is applied, and then  $Z = (\xi_{ij})_{m \times n}$ , where

$$\xi_{ij} = q-ROFWA_{\varpi}(\xi_{ij}^{(1)}, \xi_{ij}^{(2)}, \dots, \xi_{ij}^{(\ell)}) = (\sqrt[q]{1 - \prod_{k=1}^{\ell} (1 - \mu_k^q)^{\varpi_k}}, \prod_{k=1}^{\ell} (\nu_k)^{\varpi_k}). \tag{3}$$

Step 4: Proposed q-ROF-MEREC-SWARA weighting method

All the criteria are not presumed to be of equal importance. Suppose  $w = (w_1, w_2, \dots, w_n)^T$  is the weight of the criterion set with  $\sum_{j=1}^n w_j = 1$  and  $w_j \in [0, 1]$ .

**Case I.** Determination of objective weights by MEREC

Now, to find the criteria weights, the classical MEREC (Keshavarz-Ghorabae et al., 2021) model is extended under the q-ROFSs

environment. In the following, the procedure of the MEREC is presented by

Step 4a: Normalize the q-ROF-DM.

In this step, a normalized A-q-ROF-DM  $\mathbb{N} = (\varsigma_{ij})_{m \times n}$  is obtained. If  $d_b$  shows the benefit-type criteria set and  $d_n$  represents the cost-type criteria set, then we utilize the following equation for normalization:

$$\varsigma_{ij} = (\bar{\mu}_{ij}, \bar{\nu}_{ij}) = \begin{cases} \xi_{ij} = (\mu_{ij}, \nu_{ij}), & j \in d_b, \\ (\xi_{ij})^c = (\nu_{ij}, \mu_{ij}), & j \in d_n. \end{cases} \tag{4}$$

Step 4b: Find the score matrix.

With the use of the following formula, the score matrix  $\Omega = (\eta_{ij})_{m \times n}$  of each q-ROFN  $\varsigma_{ij}$  is calculated:

$$\eta_{ij} = \frac{1}{2} ((\bar{\mu}_{ij})^q - (\bar{\nu}_{ij})^q + 1). \tag{5}$$

Step 4c: Compute the overall performance of the alternatives.

This study uses a logarithmic measure with equal criteria weights to achieve the overall performance of the alternatives. Based on the normalized values attained from the former step, it can be ensured that the smaller values of  $\eta_{ij}$  yield greater performance values. This computation can be done using Eq. (6) as follows:

$$S_i = \ln \left( 1 + \left( \frac{1}{n} \sum_j |\ln(\eta_{ij})| \right) \right). \tag{6}$$

Step 4d: Compute the performance of the alternatives and the removal of each criterion.

This step involves the use of the logarithmic measure in a way similar to the former step. This step and Step 3 are different in the fact that the computation of the performance of the alternatives is done based on the separate removal of each criterion. Thus, there will be  $n$  sets of performances accompanied with  $n$  criteria. Let  $S'_i$  signify the overall performance of the  $i^{\text{th}}$  alternative concerning the  $j^{\text{th}}$  criterion removal. Eq. (7) is applied to computations performed in this step:

$$S'_{ij} = \ln \left( 1 + \left( \frac{1}{n} \sum_{k, k \neq j} |\ln(\eta_{ik})| \right) \right). \tag{7}$$

Step 4e: Compute the summation of absolute deviations.

In this step, we calculate the removal effect of the  $j^{\text{th}}$  criterion based on the values obtained from Step 3 and Step 4. Let  $V_j$  denote the effect of removing  $j^{\text{th}}$  criterion. We can calculate the values of  $V_j$  using the following formula:

$$V_j = \sum_i |S'_{ij} - S_i|. \tag{8}$$

Step 4f: Measure the final criteria weights.



The objective weight of each criterion is computed with the removal effects ( $V_j$ ) of Step 5. In the following,  $w_j^o$  represents the  $j^{\text{th}}$  criterion's weight. Eq. (9) is applied to the computation of  $w_j^o$  as follows:

$$w_j^o = \frac{V_j}{\sum_{j=1}^n V_j}, \quad j = 1(1)n. \tag{9}$$

**Case II.** Determine the subjective weights by the SWARA method

Step 4g: Estimate the crisp degrees. Eq. (1) is used to calculate the score degrees  $\mathbb{S}(\zeta_{kj})$  of q-ROFNs.

Step 4h: Prioritize the criteria. The prioritization of the attributes is done on the basis of the DE's preferences, from the attributes of the highest significance to those of the lowest significance.

Step 4i: Assess the comparative coefficient  $\kappa_j$  as follows:

$$\kappa_j = \begin{cases} 1, & j = 1 \\ \sigma_j + 1, & j > 1, \end{cases} \tag{10}$$

where  $\sigma_j$  symbolizes the importance rating.

Step 4j: The recalculated weight  $\rho_j$  is defined by

$$\rho_j = \begin{cases} 1, & j = 1 \\ \frac{\rho_{j-1}}{\kappa_j}, & j > 1. \end{cases} \tag{11}$$

Step 4k: Calculate the overall weight. The attribute weights are estimated as

$$w_j^s = \frac{\rho_j}{\sum_{j=1}^q \rho_j}, \quad j = 1(1)n. \tag{12}$$

**Case III.** Integrated weights using the q-ROF-MEREC-SWARA approach

In the A-q-ROF-decision matrix, the decision maker wants to utilize both subjective and objective weights, for the following integrated weighted equation is given.

$$w_j = \tau w_j^o + (1 - \tau) w_j^s, \quad j = 1(1)n, \tag{13}$$

where  $\tau$  is an objective factor and  $\tau \in [0, 1]$ .  $w_j^o$  represents the objective weight and  $w_j^s$  represents the subjective weight, respectively.

Step 5: Make a normalized A-q-ROF-DM (NA-q-ROF-DM)

The NA-q-ROF-DM  $\mathbb{N} = (\varsigma_{ij})_m \times n$  is obtained from  $\mathbb{Z} = (\zeta_{ij})_m \times n$ , and is given by

$$\varsigma_{ij} = (\overline{\mu}_{ij}, \overline{\nu}_{ij}) = \begin{cases} \zeta_{ij} = (\mu_{ij}, \nu_{ij}), & \text{for benefit criterion,} \\ (\zeta_{ij})^c = (\nu_{ij}, \mu_{ij}), & \text{for cost criterion.} \end{cases} \tag{14}$$

Step 6: Assess the weighted sum and power weight measures

The weighted sum measure (WSM)  $\alpha_i^{(1)}$  and weighted power measure (WPM)  $\alpha_i^{(2)}$  for each alternative are estimated as

$$\alpha_i^{(1)} = \oplus_{j=1}^n w_j \varsigma_{ij}, \quad i = 1(1)m, \tag{15}$$

$$\alpha_i^{(2)} = \otimes_{j=1}^n w_j \varsigma_{ij}, \quad i = 1(1)m. \tag{16}$$

Step 7: Relative compromise ratings of each option

The following relative compromise degree for assessing each option is derived as follows:

$$\beta_i^{(1)} = \frac{\mathbb{S}(\alpha_i^{(1)}) + \mathbb{S}(\alpha_i^{(2)})}{\sum_{i=1}^m (\mathbb{S}(\alpha_i^{(1)}) + \mathbb{S}(\alpha_i^{(2)}))}, \tag{17}$$

$$\beta_i^{(2)} = \frac{\mathbb{S}(\alpha_i^{(1)})}{\min_i \mathbb{S}(\alpha_i^{(1)})} + \frac{\mathbb{S}(\alpha_i^{(2)})}{\min_i \mathbb{S}(\alpha_i^{(2)})}, \tag{18}$$

$$\beta_i^{(3)} = \frac{\vartheta \mathbb{S}(\alpha_i^{(1)}) + (1 - \vartheta) \mathbb{S}(\alpha_i^{(2)})}{\vartheta \max_i \mathbb{S}(\alpha_i^{(1)}) + (1 - \vartheta) \max_i \mathbb{S}(\alpha_i^{(2)})}, \tag{19}$$

where,  $\vartheta$  is the strategy coefficient, and  $\vartheta \in [0, 1]$ . Generally, we take  $\vartheta = 0.5$ .

Step 8: Estimate the compromise degree

The overall compromise degree  $\beta_i$ ,  $i = 1(1)m$ , is estimated by

$$\beta_i = \frac{1}{3} (\beta_i^{(1)} + \beta_i^{(2)} + \beta_i^{(3)}) + (\beta_i^{(1)} \beta_i^{(2)} \beta_i^{(3)})^{1/3}, \quad i = 1(1)m. \tag{20}$$

The sorting of alternatives by decreasing the compromise degree  $\beta_i$ ,  $i = 1(1)m$ .

**Case study**

In this study, four steps methodology was conducted to collect the data. In the first step, an extensive survey using the current literature review and interviews with experts has been conducted to identify the main drivers to evaluate digital transformation in higher education institutions in the era of industry 4.0. In the second step, a comprehensive framework is developed to analyze and examine the important drivers for digital transformation in HEIs in the era of industry 4.0. In this regard, 27 drivers are identified to evaluate digital transformation in HEIs. In the third step, we proposed a new fuzzy decision-making approach using the q-ROF-method based on MEREC-SWARA-CoCoSo models. In this approach, the q-ROF-MEREC-SWARA is applied to compute the integrated weight of drivers for digital transformation in HEIs in the era of industry 4.0 by combining the subjective and objective weights, and the CoCoSo model is used to assess the preferences of organizations. In the fourth stage, a questionnaire is developed to collect data from academic experts. To do so, ten academic experts are invited to rank the main drivers for assessing the digital transformation in HEIs. After two-time remainders to the related experts, finally, we could collect the data from four academic experts; these four academic experts had several years of experience in the HEIs and digital services.

**Result and discussion**

Table 1, adapted from Zhang et al. (2022), depicts the significance of the DEs and attributes in the form of LVs and then converted into q-ROFNs. Table 2 presents the DEs weight based on Table 1 and Eq. (2). Table 3 defines the importance of DEs to evaluate the options and the assessments of options concerning each driver for the implementation of DT in HEIs in the era of Industry 4.0.

From Eq. (3), we make an A-q-ROF-DM  $\mathbb{Z} = (\zeta_{ij})_m \times n$ , is provided in Table 4.

To determine the criteria weights using MEREC, the overall performances of the alternatives values are computed using Eq. (5) and then presented as  $S_1 = 0.542$ ,  $S_2 = 0.549$ ,  $S_3 = 0.547$ ,  $S_4 = 0.545$ , and  $S_5 = 0.555$ . Based on Eq. (6), the alternatives' overall performances ( $S'_j$ ) are determined through the removal of each criterion; next, they are presented in Table 5. Then, the removal effects of each criterion

**Table 1**  
Performance ratings of alternatives over criteria and DEs regarding the LVs.

LVs	q-ROFNs
Absolutely high (AH)/ Extremely significant (ES)	(0.95, 0.20, 0.240)
Very very high (VVH)/ Very very significant (VVS)	(0.85, 0.30, 0.433)
Very high (VH)/ Very significant (VS)	(0.80, 0.35, 0.487)
High (H)/ Significant (S)	(0.70, 0.45, 0.554)
Moderate high (MH)/ Moderate significant (MS)	(0.60, 0.55, 0.581)
Moderate (M)/Average (A)	(0.50, 0.60, 0.624)
Moderate low (ML)/ Moderate insignificant (MI)	(0.40, 0.70, 0.592)
Low (L) / Very insignificant (VI)	(0.30, 0.75, 0.589)
Very low (VL) /Very very insignificant (VVI)	(0.20, 0.85, 0.487)
Absolutely low (AL)/ Extremely insignificant (EI)	(0.10, 0.95, 0.296)

**Table 2**  
Weight of DEs for evaluation of the alternatives.

DEs	LVs	q-ROFNs	Weights
A <sub>1</sub>	Significant (S)	(0.70, 0.45, 0.554)	0.2084
A <sub>2</sub>	Very very significant (VVS)	(0.85, 0.30, 0.433)	0.2621
A <sub>3</sub>	Very significant (VS)	(0.80, 0.35, 0.487)	0.2473
A <sub>4</sub>	Absolutely high (AH)	(0.95, 0.20, 0.240)	0.2822

on the overall performance of the alternatives are computed using the deviation-based formula of Eq. (7). The weight of each criterion is computed based on the effects of their removal on the performance  $V_j$  of the alternatives with Eq. (8). Using Eq. (9) and the  $V_j$  values, we calculate the weights of each challenge for the implementation of DT in HEIs in the era of Industry 4.0 and are given in the last column of Table 5.

From Eqs. (10) to (12), we have calculated the subjective weights using the q-ROF-SWARA procedure of each challenge for the implementation of DT in HEIs in the era of Industry 4.0 using Tables 6 and 7. The resultant values are given in Table 7 and shown in Fig. 1 and given as follows:

$$w_j^s = (0.0382, 0.0350, 0.0361, 0.0349, 0.0319, 0.0397, 0.0366, 0.0369, 0.0357, 0.0385, 0.0330, 0.0351, 0.0371, 0.0408, 0.0383, 0.0391, 0.0367, 0.0352, 0.0363, 0.0381, 0.0403, 0.0392, 0.0398, 0.0368, 0.0331, 0.0384, 0.0392)$$

From the algorithm of proposed q-ROF-MEREC-SWARA, we have to combine the q-ROF-MEREC for objective weighting and q-ROF-SWARA for subjective weighting by using Eq. (13) of different drivers for implementation of DT in HEIs in the era of Industry 4.0. The integrated weight for  $\tau = 0.5$  is shown in Fig. 1 and given as follows:

$$w_j = (0.0386, 0.0385, 0.0332, 0.0362, 0.0302, 0.0380, 0.0404, 0.0355, 0.0328, 0.0358, 0.0362, 0.0356, 0.0374, 0.0351, 0.0336, 0.0420, 0.0402, 0.0359, 0.0372, 0.0419, 0.0425, 0.0386, 0.0351, 0.0366, 0.0359, 0.0403, 0.0365)$$

Here, Fig. 1 shows the weights of diverse drivers for the implementation of DT in HEIs in the era of Industry 4.0 with respect to the goal. Developing, updating, and adapting a curriculum ( $d_{21}$ ) with a weight value of 0.0425 has come out to be the most important driver for the implementation of DT in HEIs in the era of Industry 4.0. Integration of digital technologies for universal education ( $d_{16}$ ) with a weight value of 0.0420 is the second biggest challenge for the implementation of DT in HEIs in the era of Industry 4.0. Cloud computing ( $d_{20}$ ) has third with a weight of 0.0419, 5 G networks ( $d_7$ ) has fourth with a weight of 0.0404, Internet of Things ( $d_{26}$ ) with a weight of 0.0403 has the fifth key driver for the implementation of DT in HEIs in the era of Industry 4.0, and others are considered the crucial drivers for implementation of DT in HEIs in the era of Industry 4.0.

Since all criteria are beneficial-type criteria, thus, there is no need to transform aggregated q-ROF-DM into normalized q-ROF-DM.

Using Eqs. (15) and (16), the WSM and WPM are estimated for diverse companies over different drivers for the implementation of DT in HEIs in the era of Industry 4.0. From Eqs. (17) to(20), the results of the q-ROF-MEREC-SWARA-CoCoSo method are obtained and mentioned in Table 8. Corresponding to the compromise degree ( $\beta_i$ ), the

**Table 3**  
LVs of options by DEs for drivers to implement the DT in HEIs in the era of Industry 4.0.

	HEI <sub>1</sub>	HEI <sub>2</sub>	HEI <sub>3</sub>	HEI <sub>4</sub>	HEI <sub>5</sub>
d <sub>1</sub>	(H,L,VL,M)	(M,ML,L,ML)	(MH,M,M,MH)	(H,M,H,L)	(H,VH,H,M)
d <sub>2</sub>	(ML,ML,M,MH)	(MH,VL,VL,M)	(H,M,MH,M)	(MH,M,M,ML)	(MH,H,ML,M)
d <sub>3</sub>	(MH,VH,H,M)	(MH,H,VH,M)	(M,ML,H,MH)	(M,H,MH,M)	(M,M,H,M)
d <sub>4</sub>	(M,MH,H,M)	(H,M,H,M)	(ML,ML,MH,H)	(M,MH,ML)	(H,ML,VL,M)
d <sub>5</sub>	(MH,MH,H,M)	(M,H,H,MH)	(MH,ML,M,H)	(ML,M,VH,H)	(VVH,H,H,M)
d <sub>6</sub>	(H,MH,M,MH)	(M,VL,ML,M)	(MH,H,M,MH)	(H,M,MH,ML)	(H,H,ML,MH)
d <sub>7</sub>	(ML,MH,L,M)	(L,ML,L,M)	(ML,MH,M,M)	(MH,M,ML,H)	(H,VL,ML,M)
d <sub>8</sub>	(H,VH,VH,M)	(M,VVH,VH,M)	(ML,M,MH,L)	(M,MH,L,MH)	(H,L,VL,MH)
d <sub>9</sub>	(H,MH,H,M)	(M,VH,H,MH)	(M,ML,H,ML)	(ML,H,MH,M)	(VVH,H,H,M)
d <sub>10</sub>	(ML,VH,H,MH)	(L,MH,H,M)	(M,MH,ML,H)	(MH,L,MH,H)	(VH,M,VL,M)
d <sub>11</sub>	(ML,ML,L,M)	(MH,ML,L,ML)	(MH,H,M,MH)	(H,M,MH,H)	(MH,H,M,M)
d <sub>12</sub>	(ML,L,ML,M)	(ML,MH,ML,M)	(H,VH,M,MH)	(VH,M,MH,M)	(H,M,MH,H)
d <sub>13</sub>	(MH,M,H,MH)	(M,MH,H,MH)	(M,MH,ML,M)	(MH,L,M,MH)	(H,M,VL,ML)
d <sub>14</sub>	(M,M,H,MH)	(M,MH,MH,M)	(ML,VH,MH,M)	(VH,MH,M,H)	(VVH,H,L,H)
d <sub>15</sub>	(VH,MH,M,M)	(ML,VVH,H,MH)	(M,ML,VVH,H)	(ML,VH,H,M)	(H,M,M,ML)
d <sub>16</sub>	(ML,L,L,ML)	(M,ML,VL,M)	(MH,M,VH,M)	(M,VH,H,MH)	(M,ML,L,L)
d <sub>17</sub>	(ML,ML,M,MH)	(L,L,ML,M)	(MH,ML,M,H)	(ML,M,MH,H)	(H,M,VL,VL)
d <sub>18</sub>	(MH,VH,H,MH)	(MH,VH,H,M)	(M,VL,ML,M)	(VL,ML,ML,M)	(VVH,H,L,M)
d <sub>19</sub>	(ML,M,H,MH)	(MH,VVH,H,M)	(ML,MH,M,M)	(MH,MH,L,H)	(L,VL,M,ML)
d <sub>20</sub>	(MH,M,H,MH)	(M,M,MH,MH)	(ML,VL,M,MH)	(VL,M,ML,L)	(H,L,VL,ML)
d <sub>21</sub>	(M,ML,H,M)	(M,M,ML,MH)	(M,VL,ML,H)	(L,ML,MH,L)	(H,M,VL,VL)
d <sub>22</sub>	(M,H,L,MH)	(MH,L,ML,M)	(VVH,MH,L,M)	(MH,L,H,L)	(H,H,L,ML)
d <sub>23</sub>	(MH,L,M,H)	(H,ML,VH,H)	(H,MH,L,ML)	(VH,H,M,ML)	(VH,H,M,H)
d <sub>24</sub>	(VH,MH,VL,H)	(H,VL,ML,MH)	(VH,H,ML,ML)	(VH,ML,H,MH)	(H,L,VL,L)
d <sub>25</sub>	(VH,MH,L,L)	(VH,H,L,ML)	(MH,ML,L,L)	(H,MH,L,MH)	(M,L,H,MH)
d <sub>26</sub>	(VH,MH,VL,L)	(VH,MH,VL,L)	(M,VH,VL,L)	(MH,ML,VL,L)	(M,VH,VL,L)
d <sub>27</sub>	(ML,L,M,MH)	(VH,VH,ML,H)	(H,MH,M,MH)	(VH,MH,L,ML)	(H,MH,M,MH)

**Table 4**  
The A-q-ROF-DM for drivers to implement the DT in HEIs in the era of Industry 4.0.

	HEI <sub>1</sub>	HEI <sub>2</sub>	HEI <sub>3</sub>	HEI <sub>4</sub>	HEI <sub>5</sub>
d <sub>1</sub>	(0.476, 0.653, 0.589)	(0.404, 0.690, 0.601)	(0.553, 0.575, 0.603)	(0.579, 0.560, 0.592)	(0.694, 0.457, 0.557)
d <sub>2</sub>	(0.494, 0.629, 0.600)	(0.421, 0.704, 0.573)	(0.578, 0.553, 0.600)	(0.501, 0.615, 0.609)	(0.571, 0.568, 0.594)
d <sub>3</sub>	(0.675, 0.476, 0.563)	(0.673, 0.478, 0.564)	(0.573, 0.568, 0.591)	(0.590, 0.545, 0.596)	(0.564, 0.559, 0.608)
d <sub>4</sub>	(0.588, 0.546, 0.596)	(0.609, 0.526, 0.593)	(0.564, 0.582, 0.586)	(0.490, 0.625, 0.608)	(0.492, 0.641, 0.589)
d <sub>5</sub>	(0.606, 0.536, 0.587)	(0.641, 0.506, 0.578)	(0.574, 0.566, 0.592)	(0.652, 0.500, 0.570)	(0.706, 0.449, 0.547)
d <sub>6</sub>	(0.604, 0.539, 0.587)	(0.421, 0.683, 0.597)	(0.611, 0.533, 0.586)	(0.559, 0.578, 0.594)	(0.620, 0.531, 0.577)
d <sub>7</sub>	(0.477, 0.640, 0.603)	(0.395, 0.692, 0.605)	(0.513, 0.606, 0.608)	(0.575, 0.564, 0.592)	(0.491, 0.643, 0.588)
d <sub>8</sub>	(0.724, 0.429, 0.540)	(0.720, 0.438, 0.539)	(0.469, 0.646, 0.602)	(0.528, 0.605, 0.597)	(0.510, 0.637, 0.578)
d <sub>9</sub>	(0.630, 0.514, 0.582)	(0.680, 0.473, 0.560)	(0.524, 0.608, 0.597)	(0.577, 0.562, 0.593)	(0.706, 0.449, 0.547)
d <sub>10</sub>	(0.670, 0.489, 0.558)	(0.565, 0.572, 0.595)	(0.578, 0.564, 0.590)	(0.585, 0.564, 0.584)	(0.562, 0.584, 0.585)
d <sub>11</sub>	(0.413, 0.682, 0.604)	(0.436, 0.677, 0.593)	(0.611, 0.533, 0.586)	(0.635, 0.510, 0.580)	(0.587, 0.546, 0.598)
d <sub>12</sub>	(0.411, 0.682, 0.604)	(0.492, 0.629, 0.601)	(0.674, 0.479, 0.563)	(0.617, 0.525, 0.586)	(0.635, 0.510, 0.580)
d <sub>13</sub>	(0.608, 0.535, 0.587)	(0.612, 0.533, 0.584)	(0.510, 0.609, 0.607)	(0.520, 0.610, 0.599)	(0.490, 0.643, 0.588)
d <sub>14</sub>	(0.590, 0.545, 0.596)	(0.555, 0.574, 0.602)	(0.625, 0.527, 0.576)	(0.668, 0.483, 0.566)	(0.694, 0.469, 0.546)
d <sub>15</sub>	(0.619, 0.524, 0.585)	(0.697, 0.470, 0.542)	(0.677, 0.485, 0.554)	(0.644, 0.508, 0.572)	(0.534, 0.590, 0.605)
d <sub>16</sub>	(0.354, 0.725, 0.591)	(0.423, 0.681, 0.598)	(0.628, 0.516, 0.582)	(0.680, 0.473, 0.560)	(0.380, 0.703, 0.601)
d <sub>17</sub>	(0.494, 0.629, 0.600)	(0.394, 0.692, 0.605)	(0.554, 0.566, 0.611)	(0.581, 0.559, 0.591)	(0.460, 0.680, 0.572)
d <sub>18</sub>	(0.693, 0.465, 0.552)	(0.675, 0.476, 0.563)	(0.421, 0.683, 0.597)	(0.404, 0.698, 0.591)	(0.650, 0.509, 0.565)
d <sub>19</sub>	(0.577, 0.563, 0.592)	(0.701, 0.458, 0.547)	(0.513, 0.606, 0.608)	(0.587, 0.561, 0.583)	(0.374, 0.719, 0.585)
d <sub>20</sub>	(0.608, 0.535, 0.587)	(0.557, 0.573, 0.601)	(0.465, 0.662, 0.587)	(0.377, 0.714, 0.590)	(0.448, 0.682, 0.578)
d <sub>21</sub>	(0.546, 0.582, 0.603)	(0.512, 0.608, 0.606)	(0.512, 0.630, 0.584)	(0.428, 0.682, 0.593)	(0.460, 0.680, 0.572)
d <sub>22</sub>	(0.566, 0.574, 0.592)	(0.464, 0.649, 0.603)	(0.622, 0.536, 0.571)	(0.517, 0.620, 0.591)	(0.568, 0.578, 0.586)
d <sub>23</sub>	(0.562, 0.576, 0.594)	(0.683, 0.475, 0.555)	(0.530, 0.610, 0.589)	(0.632, 0.519, 0.575)	(0.692, 0.459, 0.558)
d <sub>24</sub>	(0.641, 0.527, 0.558)	(0.523, 0.628, 0.576)	(0.618, 0.540, 0.571)	(0.651, 0.507, 0.565)	(0.427, 0.695, 0.578)
d <sub>25</sub>	(0.562, 0.590, 0.580)	(0.608, 0.549, 0.573)	(0.415, 0.690, 0.593)	(0.578, 0.570, 0.584)	(0.561, 0.578, 0.593)
d <sub>26</sub>	(0.554, 0.608, 0.568)	(0.554, 0.608, 0.568)	(0.553, 0.605, 0.573)	(0.401, 0.712, 0.576)	(0.553, 0.605, 0.573)
d <sub>27</sub>	(0.477, 0.641, 0.601)	(0.714, 0.446, 0.539)	(0.576, 0.579, 0.578)	(0.576, 0.579, 0.578)	(0.604, 0.539, 0.587)

prioritization of companies over different drivers for implementation of DT in HEIs in the era of Industry 4.0 is  $HEI_4 \succ HEI_3 \succ HEI_5 \succ HEI_1 \succ HEI_2$ , and thus, the higher education institution (HEI)–4 ( $HEI_4$ ) is the ideal HEI over different drivers for implementation of DT in HEIs in the era of Industry 4.0.

*Sensitivity analysis*

The present study also involves a sensitivity analysis to investigate how the developed method achieves its objectives. This study analyzed the impact of the variation of the coefficient  $\vartheta$  ( $0 \leq \vartheta \leq 1$ ) over the drivers arising when implementing DT in HEIs in the era of Industry 4.0; Fig 2 presents the compromise degree of the companies. In addition, the compromise degrees for each company were determined with diverse parameter  $\vartheta$  value. Accordingly, it could be concluded that the companies' over-diverse drivers arising when implementing DT in HEIs in the era of Industry 4.0 are dependent upon and are sensitive to different parameter  $\vartheta$ . For that reason, the q-ROF-MEREC-SWARA-CoCoSo model was confirmed as desirably stable with various values of  $\vartheta$ . Based on the information presented in Table 9 and Fig. 2, option  $HEI_4$  gained the first rank, while  $HEI_2$  gained the last one. According to the results of this analysis, the q-ROF-MEREC-SWARA-CoCoSo method does not depend upon any bias, and the results achieved in the current paper have enough stability in their nature.

*Comparative discussion*

Here, the proposed method is compared with diverse extant approaches. To demonstrate the efficacy and the unique advantages of the developed method, the q-ROF-WASPAS (Rani & Mishra, 2020) and q-ROF-COPRAS (Krishankumar et al., 2021) are taken to tackle the same problem.

*q-ROF-WASPAS model*

Step 1-Step 6: Same as the aforementioned approach.

Step 7: The utility degree (UD) of WASPAS measure of each choice is computed by

$$\alpha_i = \lambda \alpha_i^{(1)} + (1 - \lambda) \alpha_i^{(2)}, \quad i = 1(1)m, \quad (21)$$

where  $\lambda \in [0, 1]$

stands for the strategy coefficient.

**Table 5**  
The implementation of the MEREC weighting approach for computing the criteria weights.

Drivers	$(S_j)$ values					$V_j$	$w_j^*$
	HEI <sub>1</sub>	HEI <sub>2</sub>	HEI <sub>3</sub>	HEI <sub>4</sub>	HEI <sub>5</sub>		
d <sub>1</sub>	0.522	0.525	0.531	0.530	0.545	0.083	0.0389
d <sub>2</sub>	0.524	0.525	0.532	0.527	0.540	0.089	0.0419
d <sub>3</sub>	0.532	0.538	0.532	0.531	0.540	0.065	0.0304
d <sub>4</sub>	0.528	0.536	0.531	0.526	0.536	0.080	0.0376
d <sub>5</sub>	0.529	0.537	0.532	0.533	0.546	0.061	0.0285
d <sub>6</sub>	0.529	0.526	0.534	0.529	0.542	0.077	0.0363
d <sub>7</sub>	0.523	0.525	0.529	0.530	0.536	0.094	0.0442
d <sub>8</sub>	0.534	0.540	0.527	0.528	0.537	0.073	0.0341
d <sub>9</sub>	0.530	0.538	0.530	0.530	0.546	0.064	0.0299
d <sub>10</sub>	0.531	0.533	0.532	0.530	0.540	0.071	0.0332
d <sub>11</sub>	0.520	0.527	0.534	0.533	0.541	0.084	0.0393
d <sub>12</sub>	0.520	0.530	0.536	0.532	0.543	0.077	0.0361
d <sub>13</sub>	0.529	0.536	0.529	0.527	0.536	0.080	0.0377
d <sub>14</sub>	0.528	0.533	0.534	0.534	0.545	0.063	0.0295
d <sub>15</sub>	0.529	0.539	0.536	0.533	0.539	0.061	0.0289
d <sub>16</sub>	0.516	0.526	0.534	0.534	0.531	0.095	0.0449
d <sub>17</sub>	0.524	0.525	0.532	0.530	0.534	0.093	0.0437
d <sub>18</sub>	0.532	0.538	0.524	0.521	0.543	0.078	0.0367
d <sub>19</sub>	0.528	0.539	0.529	0.530	0.530	0.081	0.0381
d <sub>20</sub>	0.527	0.533	0.526	0.520	0.533	0.097	0.0458
d <sub>21</sub>	0.526	0.531	0.529	0.523	0.534	0.095	0.0446
d <sub>22</sub>	0.527	0.529	0.534	0.527	0.540	0.081	0.0381
d <sub>23</sub>	0.527	0.538	0.530	0.532	0.545	0.065	0.0305
d <sub>24</sub>	0.530	0.531	0.534	0.533	0.532	0.077	0.0364
d <sub>25</sub>	0.527	0.535	0.524	0.530	0.540	0.082	0.0387
d <sub>26</sub>	0.526	0.532	0.530	0.520	0.539	0.090	0.0422
d <sub>27</sub>	0.523	0.539	0.532	0.530	0.542	0.072	0.0339

**Table 6**  
Significance degree of drivers for implementation of DT in HEIs in the era of Industry 4.0.

Drivers	A <sub>1</sub>	A <sub>2</sub>	A <sub>3</sub>	A <sub>4</sub>	A-q-ROFNs	S( $\xi_{kj}$ )
d <sub>1</sub>	MH	M	M	MH	(0.553, 0.575, 0.603)	0.488
d <sub>2</sub>	M	M	M	L	(0.456, 0.639, 0.619)	0.400
d <sub>3</sub>	M	MH	L	M	(0.495, 0.620, 0.609)	0.431
d <sub>4</sub>	MH	L	ML	M	(0.464, 0.649, 0.603)	0.397
d <sub>5</sub>	L	ML	L	ML	(0.359, 0.722, 0.591)	0.303
d <sub>6</sub>	M	H	MH	M	(0.590, 0.545, 0.596)	0.526
d <sub>7</sub>	ML	M	H	L	(0.513, 0.615, 0.600)	0.443
d <sub>8</sub>	MH	M	L	MH	(0.522, 0.608, 0.599)	0.452
d <sub>9</sub>	ML	M	MH	ML	(0.487, 0.633, 0.601)	0.418
d <sub>10</sub>	H	M	ML	MH	(0.565, 0.573, 0.594)	0.496
d <sub>11</sub>	L	VL	MH	ML	(0.416, 0.704, 0.576)	0.339
d <sub>12</sub>	ML	M	MH	L	(0.469, 0.646, 0.602)	0.402
d <sub>13</sub>	H	ML	L	MH	(0.534, 0.607, 0.589)	0.458
d <sub>14</sub>	H	L	ML	VH	(0.626, 0.535, 0.568)	0.553
d <sub>15</sub>	MH	H	L	M	(0.559, 0.577, 0.595)	0.489
d <sub>16</sub>	ML	H	M	MH	(0.580, 0.561, 0.591)	0.511
d <sub>17</sub>	ML	H	M	L	(0.517, 0.612, 0.599)	0.446
d <sub>18</sub>	L	M	MH	ML	(0.474, 0.643, 0.602)	0.406
d <sub>19</sub>	M	ML	H	L	(0.508, 0.620, 0.598)	0.437
d <sub>20</sub>	MH	M	MH	M	(0.550, 0.577, 0.604)	0.485
d <sub>21</sub>	M	ML	M	VH	(0.610, 0.537, 0.583)	0.542
d <sub>22</sub>	H	H	M	L	(0.583, 0.558, 0.591)	0.514
d <sub>23</sub>	M	H	M	MH	(0.593, 0.543, 0.595)	0.529
d <sub>24</sub>	M	ML	L	H	(0.523, 0.609, 0.597)	0.451
d <sub>25</sub>	M	ML	ML	L	(0.401, 0.691, 0.601)	0.342
d <sub>26</sub>	M	MH	M	MH	(0.559, 0.572, 0.600)	0.492
d <sub>27</sub>	H	ML	MH	MH	(0.587, 0.562, 0.583)	0.514

Step 8: Rank the alternatives according to the decreasing values of  $\alpha_i$ ,  $i = 1(1)m$ .

Step 7-Step 8: Form Eq. (21), the UD ( $\alpha_i$ ) degree for each HEI option is demonstrated and depicted in Table 10. Hence, the priority order of the HEIs is obtained as  $HEI_4 \setminus succHEI_3 \setminus succHEI_5 \setminus succHEI_1 \setminus succHEI_2$  and, HEI-4 is the most desirable option.

**Table 7**  
The weight of different drivers for implementation of DT in HEIs by the SWARA method.

Drivers	S( $\xi_{kj}$ )	Comparative importance of attributes ( $S_j$ )	Coefficient ( $k_j$ )	Recalculated weight ( $\rho_j$ )	$w_j^*$
d <sub>14</sub>	0.553	–	1.000	1.000	0.0408
d <sub>21</sub>	0.542	0.011	1.011	0.9891	0.0403
d <sub>23</sub>	0.529	0.013	1.013	0.9764	0.0398
d <sub>6</sub>	0.526	0.003	1.003	0.9735	0.0397
d <sub>22</sub>	0.514	0.012	1.012	0.9620	0.0392
d <sub>27</sub>	0.514	0.000	1.000	0.9620	0.0392
d <sub>16</sub>	0.511	0.003	1.003	0.9591	0.0391
d <sub>10</sub>	0.496	0.015	1.015	0.9449	0.0385
d <sub>26</sub>	0.492	0.004	1.004	0.9411	0.0384
d <sub>15</sub>	0.489	0.003	1.003	0.9383	0.0383
d <sub>1</sub>	0.488	0.001	1.001	0.9374	0.0382
d <sub>20</sub>	0.485	0.003	1.003	0.9346	0.0381
d <sub>13</sub>	0.458	0.027	1.027	0.9100	0.0371
d <sub>8</sub>	0.452	0.006	1.006	0.9046	0.0369
d <sub>24</sub>	0.451	0.001	1.001	0.9037	0.0368
d <sub>17</sub>	0.446	0.005	1.005	0.8992	0.0367
d <sub>7</sub>	0.443	0.003	1.003	0.8965	0.0366
d <sub>19</sub>	0.437	0.006	1.006	0.8912	0.0363
d <sub>3</sub>	0.431	0.006	1.006	0.8859	0.0361
d <sub>9</sub>	0.418	0.013	1.013	0.8745	0.0357
d <sub>18</sub>	0.406	0.012	1.012	0.8641	0.0352
d <sub>12</sub>	0.402	0.004	1.004	0.8607	0.0351
d <sub>2</sub>	0.400	0.002	1.002	0.8590	0.0350
d <sub>4</sub>	0.397	0.003	1.003	0.8564	0.0349
d <sub>25</sub>	0.342	0.055	1.055	0.8118	0.0331
d <sub>11</sub>	0.339	0.003	1.003	0.8094	0.0330
d <sub>5</sub>	0.303	0.036	1.036	0.7813	0.0319

*q-ROF-COPRAS model*

Step 1-Step 4: Same as the above-discussed method.

Step 5: We compute the assessment rating for each option to maximize the benefit rating  $\beta_i = \oplus^n_{j=1} w_j \xi_{ij}$ ,  $i = 1(1)m$ . Also, the relative degree (RD) of each option is similar to the  $\beta_i$ ,  $i = 1(1)m$ . Therefore, we obtain  $RD_1 = 0.243$ ,  $RD_2 = 0.240$ ,  $RD_3 = 0.246$ ,  $RD_4 = 0.249$ , and  $RD_5 = 0.244$ .

Step 6: Assess the RDs of the five HEIs using the priority  $RD_i$ ,  $i = 1(1)m$  and obtain the prioritization order of the HEIs as  $RD_4 \setminus succRD_3 \setminus succRD_5 \setminus succRD_1 \setminus succRD_2$ . The option HEI-4 is the optimal one among the others.

Step 7: Estimate the “utility degree”  $u_i = \frac{RD_i}{RD_{max}} \times 100\%$ . Then, we obtain  $u_1 = 97.60\%$ ,  $u_2 = 96.39\%$ ,  $u_3 = 98.80\%$ ,  $u_4 = 100.00\%$  and  $u_5 = 97.99\%$ .

Here, a comparison is made between the proposed method and some extant methods, including q-ROF-WASPAS and q-ROF-COPRAS, which is depicted in Fig. 3. By comparing with the q-ROF-COPRAS method, the final ranking of the HEIs is  $HEI_4 \setminus succHEI_3 \setminus succHEI_5 \setminus succHEI_1 \setminus succHEI_2$ , and the best HEI is  $HEI_4$  for the different drivers for implementation of DT in HEIs in the era of Industry 4.0. Hence, we observe that the optimal HEI is the same with all the proposed q-ROF-COPRAS and q-ROF-WASPAS models, while the prioritization results slightly vary with diverse extant models. In general, the advantages of the “q-ROF-MEREC-SWARA-CoCoSo” approach over the existing methods are presented as follows:

- The subjective and objective weights of criteria in the present research were assessed by the q-ROF-MEREC-SWARA method as q-ROFNs by DEs, whereas in q-ROF-COPRAS, the criteria weights were calculated by a linear programming model, and in q-ROF-



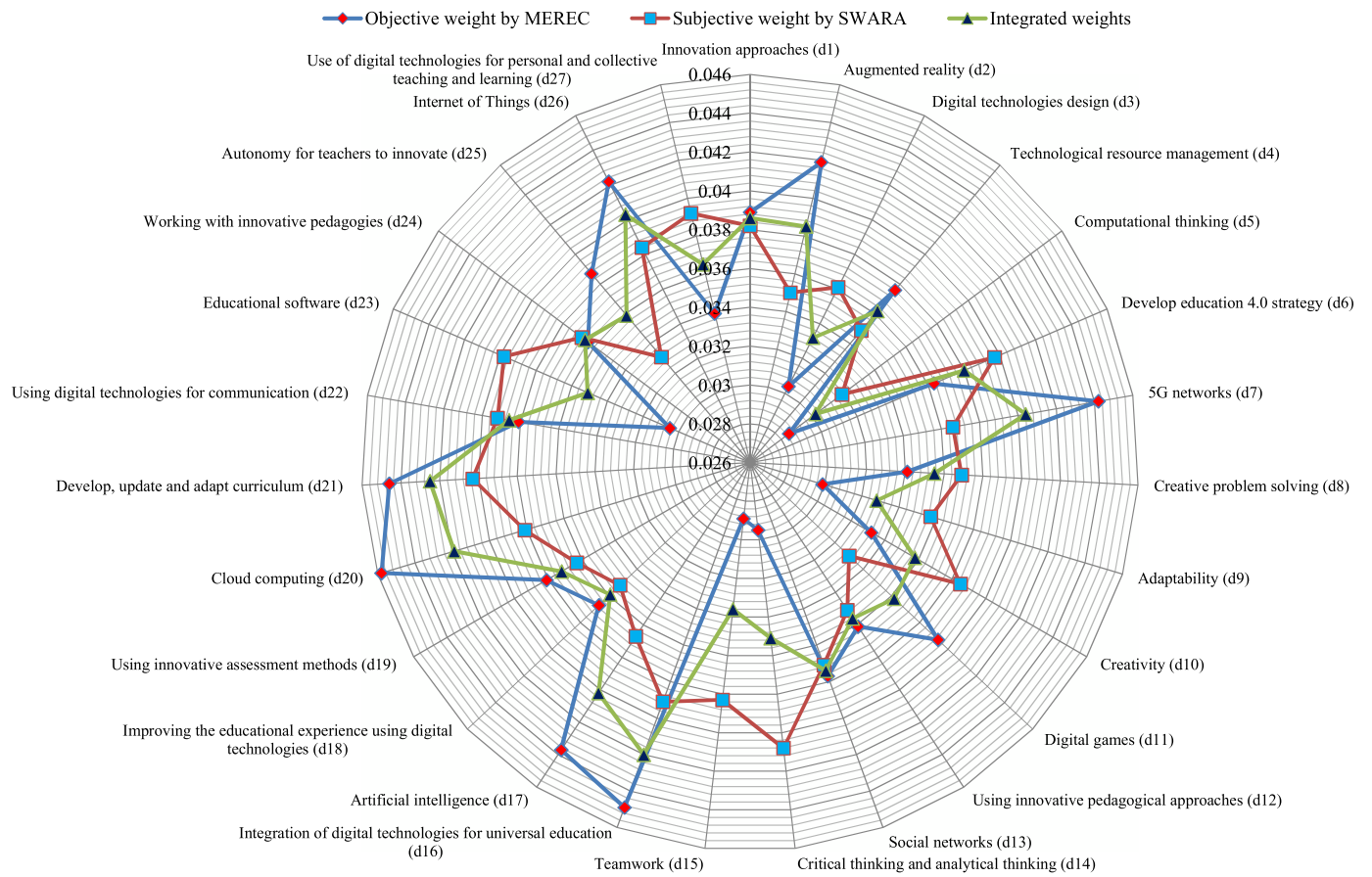


Fig. 1. Weight values of different drivers for implementation of DT in HEIs in the era of Industry 4.0.

Table 8  
Overall results of the developed method.

HEIs	$\alpha_i^{(1)}$	$\alpha_i^{(2)}$	$\mathcal{S}(\alpha_i^{(1)})$	$\mathcal{S}(\alpha_i^{(2)})$	$\beta_i^{(1)}$	$\beta_i^{(2)}$	$\beta_i^{(3)}$	$\beta_i$	Ranking
$I_1$	(0.549, 0.601, 0.581)	(0.572, 0.571, 0.589)	0.470	0.501	0.199	2.026	0.975	1.799	4
$I_2$	(0.548, 0.603, 0.580)	(0.561, 0.579, 0.591)	0.469	0.490	0.196	2.000	0.962	1.776	5
$I_3$	(0.549, 0.598, 0.584)	(0.581, 0.563, 0.588)	0.472	0.510	0.201	2.047	0.985	1.818	2
$I_4$	(0.558, 0.591, 0.582)	(0.586, 0.559, 0.587)	0.481	0.515	0.204	2.078	1.000	1.845	1
$I_5$	(0.556, 0.598, 0.577)	(0.574, 0.574, 0.584)	0.476	0.500	0.200	2.035	0.979	1.807	3

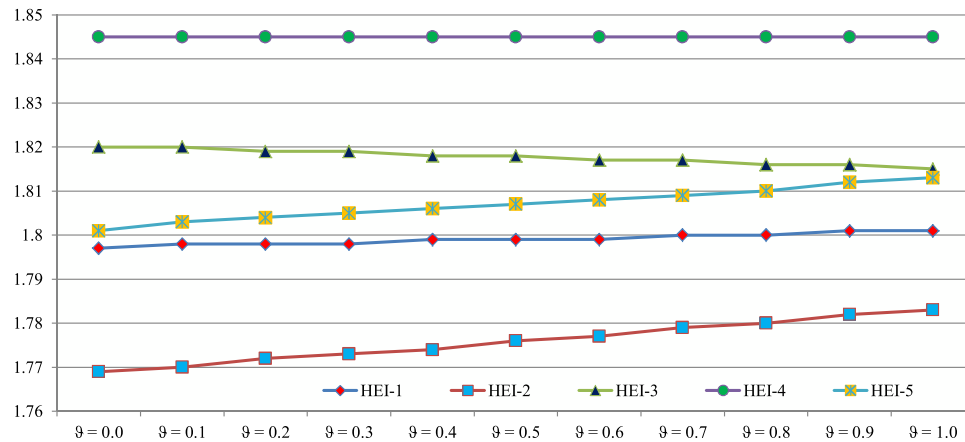


Fig. 2. The compromise degrees of the company over  $\vartheta$  values.

**Table 9**  
Compromise degrees of the company over values of  $\vartheta$ .

HEIs	$\vartheta = 0.0$	$\vartheta = 0.1$	$\vartheta = 0.2$	$\vartheta = 0.3$	$\vartheta = 0.4$	$\vartheta = 0.5$	$\vartheta = 0.6$	$\vartheta = 0.7$	$\vartheta = 0.8$	$\vartheta = 0.9$	$\vartheta = 1.0$
HEI <sub>1</sub>	1.797	1.798	1.798	1.798	1.799	1.799	1.799	1.800	1.800	1.801	1.801
HEI <sub>2</sub>	1.769	1.770	1.772	1.773	1.774	1.776	1.777	1.779	1.780	1.782	1.783
HEI <sub>3</sub>	1.820	1.820	1.819	1.819	1.818	1.818	1.817	1.817	1.816	1.816	1.815
HEI <sub>4</sub>	1.845	1.845	1.845	1.845	1.845	1.845	1.845	1.845	1.845	1.845	1.845
HEI <sub>5</sub>	1.801	1.803	1.804	1.805	1.806	1.807	1.808	1.809	1.810	1.812	1.813

**Table 10**  
Results of the q-ROF-WASPAS model for different HEIs.

Options	WSM		WPM		UD $\alpha_i(\lambda)$	Ranking
	$\alpha_i^{(1)}$	$S(\alpha_i^{(1)})$	$\alpha_i^{(2)}$	$S(\alpha_i^{(2)})$		
HEI <sub>1</sub>	(0.549, 0.601, 0.581)	0.470	(0.572, 0.571, 0.589)	0.501	0.486	4
HEI <sub>2</sub>	(0.548, 0.603, 0.580)	0.469	(0.561, 0.579, 0.591)	0.490	0.479	5
HEI <sub>3</sub>	(0.549, 0.598, 0.584)	0.472	(0.581, 0.563, 0.588)	0.510	0.491	2
HEI <sub>4</sub>	(0.558, 0.591, 0.582)	0.481	(0.586, 0.559, 0.587)	0.515	0.498	1
HEI <sub>5</sub>	(0.556, 0.598, 0.577)	0.476	(0.574, 0.574, 0.584)	0.500	0.488	3

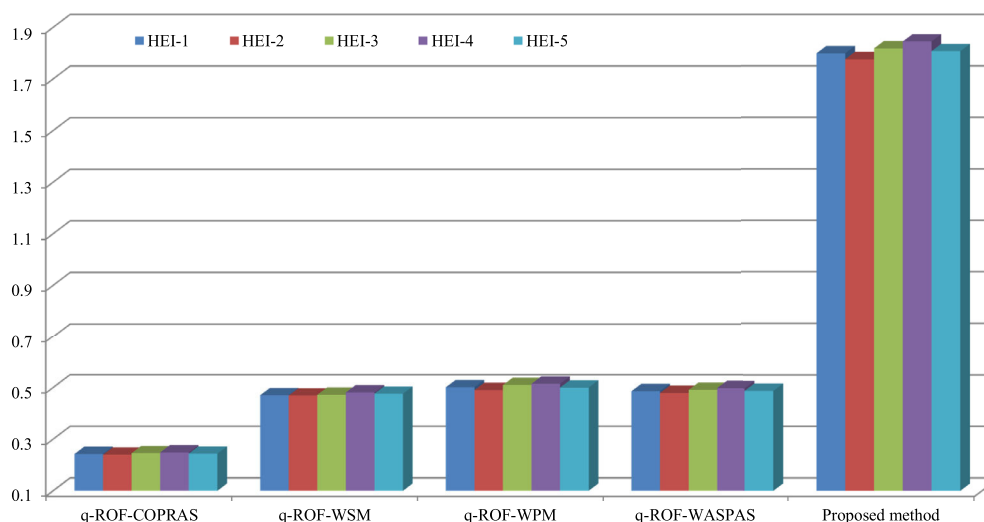
WASPAS, the criteria weight are computed by similarity measure-based weighting procedure.

- The q-ROFSs can reflect the DE's indecision more accurately than further conventional extensions of FSs. Therefore, the use of the developed q-ROF-MEREC-SWARA-CoCoSo approach gives a more flexible way to express the uncertainty to evaluate the drivers for the implementation of DT in HEIs in the era of Industry 4.0.
- The SWARA model is used to estimate the subjective weights, and MEREC is applied to determine the objective weights of drivers in the evaluation of the drivers for implementation of DT in HEIs in the era of Industry 4.0, which creates the developed q-ROF-MEREC-SWARA-CoCoSo model more reliable, effective and sensible tool.

**Conclusions**

In the recent decade, the DT has been recognized as a priority for HEIs; this process is necessary for all the organizations claiming to be change leaders and competitive in their relevant domains. Several scholars have focused on the definition of DT when it comes to the field of business. To persist in time, HEIs require evolving in an

integral manner. Additionally, two challenging tasks are exploiting all the changes provided by the wealth of DTs and redefining the entire business models across the whole value chain. Such a challenge is more persistent in the case of those organizations that are enduringly attempting to make sure of their competitive positions in the international market. However, numerous universities attempt to develop definite digital strategies to be well adapted to the substantial changes in the use of new technologies, but these institutions still lack the capability, vision, or commitment to implement these technologies effectively. In this regard, there is a need to gain an inclusive vision of the whole DT in HEIs in a way to achieve an overview of the current state of DT in these institutions. It is also important to identify the distinctive features of DT, such as actors, dimensions, and implementations, when it occurs in an HEI. Remember that DT in HEIs has been investigated from various points of view, and the literature still lacks a consensus on its definition. To examine, rank, and evaluate the drivers for implementation of DT in HEIs in the era of Industry 4.0, this study introduced an MCDM framework on q-ROFSs. In this regard, an integrated framework using the q-ROF-MEREC-SWARA and CoCoSo approaches called q-ROF-MEREC-SWARA-CoCoSo is discussed. To rank the drivers for implementation of DT in HEIs in the era of Industry 4.0, the q-ROF-MEREC-SWARA is applied, and to



**Fig. 3.** Comparison of significance degrees of each HEI with extant methods.

estimate the preference order of different industries over the different drivers for implementation of DT in HEIs in the era of Industry 4.0, the CoCoSo method is used. To validate the results of this study, a comparison with the q-ROF-WASPAS, q-ROF-COPRAS, q-ROF-WPM, and q-ROF-WSM methods is conducted.

## References

- Abad-Segura, E., González-Zamar, M. D., Infante-Moro, J. C., & Ruipérez García, G. (2020). Sustainable management of digital transformation in higher education: Global research trends. *Sustainability*, 12(5), 2107. <https://www.mdpi.com/2071-1050/12/5/2107>.
- Alhubaishy, A., & Aljuhani, A. (2021). The challenges of instructors' and students' attitudes in digital transformation: A case study of Saudi Universities. *Education and Information Technologies*, 26(4), 4647–4662. doi:10.1007/s10639-021-10491-6.
- Archer, K., Savage, R., Sanghera-Sidhu, S., Wood, E., Gottardo, A., & Chen, V. (2014). Examining the effectiveness of technology use in classrooms: A tertiary meta-analysis. *Computers & Education*, 78, 140–149. doi:10.1016/j.compedu.2014.06.001.
- Babbitt, C. W. (2018). Communicating science for clean technology. *Clean Technologies and Environmental Policy*, 20(8), 1735–1736. doi:10.1007/s10098-018-1608-1.
- Ballestar, M. T., Camiña, E., Díaz-Chao, A., & Torrent-Sellens, J. (2021). Productivity and employment effects of digital complementarities. *Journal of Innovation & Knowledge*, 6(3), 177–190. doi:10.1016/j.jik.2020.10.006.
- Benavides, L. M. C., Tamayo Arias, J. A., Arango Serna, M. D., Branch Bedoya, J. W., & Burgos, D. (2020). Digital transformation in higher education institutions: A systematic literature review. *Sensors*, 20(11), 3291. <https://www.mdpi.com/1424-8220/20/11/3291>.
- Boelens, R., De Wever, B., & Voet, M. (2017). Four key challenges to the design of blended learning: A systematic literature review. *Educational Research Review*, 22, 1–18. doi:10.1016/j.edurev.2017.06.001.
- Bond, M., Marín, V. I., Dolch, C., Bedenlier, S., & Zawacki-Richter, O. (2018). Digital transformation in German higher education: Student and teacher perceptions and usage of digital media. *International Journal of Educational Technology in Higher Education*, 15(1), 48. doi:10.1186/s41239-018-0130-1.
- Bresinsky, M., von Reusner, F., Brooks, A., Brooks, E., & Vidakis, N. (2018). GLOBE – learn and innovate digitization by a virtual collaboration exercise and living lab. *Interactivity, game creation, design, learning, and innovation. artsit dli 2017 2017. Lecture notes of the institute for computer sciences, social informatics and telecommunications engineering, vol 229*. Cham: Springer. doi:10.1007/978-3-319-76908-0\_26.
- Bygstad, B., Øvrelid, E., Ludvigsen, S., & Dæhlen, M. (2022). From dual digitalization to digital learning space: Exploring the digital transformation of higher education. *Computers & Education*, 182, 104463. doi:10.1016/j.compedu.2022.104463.
- Cheung, A. C. K., & Slavina, R. E. (2013). The effectiveness of educational technology applications for enhancing mathematics achievement in K-12 classrooms: A meta-analysis. *Educational Research Review*, (9), 88–113. doi:10.1016/j.edurev.2013.01.001.
- Choi, M., Cristol, D., & Gimbert, B. (2018). Teachers as digital citizens: The influence of individual backgrounds, internet use and psychological characteristics on teachers' levels of digital citizenship. *Computers & Education*, 121, 143–161. doi:10.1016/j.compedu.2018.03.005.
- de Koster, S., Volman, M., & Kuiper, E. (2017). Concept-guided development of technology in 'traditional' and 'innovative' schools: Quantitative and qualitative differences in technology integration. *Educational Technology Research and Development*, 65(5), 1325–1344. doi:10.1007/s11423-017-9527-0.
- Detyna, M., & Kadiri, M. (2020). Virtual reality in the HE classroom: Feasibility, and the potential to embed in the curriculum. *Journal of Geography in Higher Education*, 44(3), 474–485. doi:10.1080/03098265.2019.1700486.
- Easterday, M. W., Rees Lewis, D. G., & Gerber, E. M. (2018). The logic of design research. *Learning: Research and Practice*, 4(2), 131–160. doi:10.1080/23735082.2017.1286367.
- Elena, F. (2017). Embedding digital teaching and learning practices in the modernization of higher education institutions. *International Multidisciplinary Scientific Geo-Conference: SCGM*, 17, 41–47.
- Englund, C., Olofsson, A. D., & Price, L. (2017). Teaching with technology in higher education: Understanding conceptual change and development in practice. *Higher Education Research & Development*, 36(1), 73–87. doi:10.1080/07294360.2016.1171300.
- European, C., Joint Research, C., & Redecker, C. (2017). *European framework for the digital competence of educators: DigCompedu*. Publications Office. doi:10.2760/178382.
- Falco, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy*, 50(7), 104064. doi:10.1016/j.respol.2020.104064.
- Faria, J. A., & Nôvoa, H. (2017). *Digital transformation at the university of porto*. 2017//, Cham: Exploring Services Science.
- Formánková, S., Kučerová, R., & Hrdličková, A. (2018). International standards of social responsibility and their suitability for high educational institutions. *World Review of Entrepreneurship, Management and Sustainable Development*, 14(1–2), 156–170. doi:10.1504/WREMSD.2018.089072.
- García, C. M., Domínguez, C. Y., & Ruiz, C. M. (2015). University teaching with digital technologies. *Comunicar Media Education Research Journal*, 23(2).
- Gobble, M. M. (2018). Digital strategy and digital transformation. *Research-Technology Management*, 61(5), 66–71. doi:10.1080/08956308.2018.1495969.
- Grab, B., Olaru, M., & Gavril, R. (2019). Self-managed teams as a key to unlocking digital transformation in business management. *Quality-Access to Success*, 20, 280–286.
- Gurung, B., & Rutledge, D. (2014). Digital learners and the overlapping of their personal and educational digital engagement. *Computers & Education*, 77, 91–100. doi:10.1016/j.compedu.2014.04.012.
- Ha, L. T., & Thanh, T. T. (2022). Effects of digital public services on trades in green goods: Does institutional quality matter? *Journal of Innovation & Knowledge*, 7(1), 100168. doi:10.1016/j.jik.2022.100168.
- Heredia, J., Castillo-Vergara, M., Geldes, C., Carbajal Gamarra, F. M., Flores, A., & Heredia, W. (2022). How do digital capabilities affect firm performance? The mediating role of technological capabilities in the "new normal". *Journal of Innovation & Knowledge*, 7(2), 100171. doi:10.1016/j.jik.2022.100171.
- Hong, C., & Ma, W. W. K. (2020). Introduction: Education 4.0: Applied degree education and the future of work. C. Hong & W. W. K. Ma, *Applied degree education and the future of work: Education 4.0*. C. Hong & W. W. K. Ma. (pp. 1–13). Singapore: Springer. doi:10.1007/978-981-15-3142-2\_1.
- Jääskelä, P., Häkkinen, P., & Rasku-Puttonen, H. (2017). Teacher beliefs regarding learning, pedagogy, and the use of technology in higher education. *Journal of Research on Technology in Education*, 49(3–4), 198–211. doi:10.1080/15391523.2017.1343691.
- Javed, A. R., Shahzad, F., Rehman, S. U., Zikria, Y. B., Razzak, I., Jalil, Z., et al. (2022). Future smart cities: Requirements, emerging technologies, applications, challenges, and future aspects. *Cities (London, England)*, 129, 103794. doi:10.1016/j.cities.2022.103794.
- Kaminskyi, O. Y., Yereshko, Y. O., & Kyrychenko, S. O. (2018). Digital transformation of university education in Ukraine: Trajectories of development in the conditions of new technological and economic order. *унформационна технологія з засоби навчання*, 64(2), 128–137 №.
- Kersulienė, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *Journal of Business Economics and Management*, 11(2), 243–258. doi:10.3846/jbem.2010.12.
- Keshavarz-Ghorabae, M., Amiri, M., Zavadskas, E. K., Turskis, Z., & Antucheviciene, J. (2021). Determination of objective weights using a new method based on the removal effects of criteria (MEREK). *Symmetry*, 13(4), 525. <https://www.mdpi.com/2073-8994/13/4/525>.
- Kirkwood, A. (2009). E-learning: You don't always get what you hope for. *Technology, Pedagogy and Education*, 18(2), 107–121. doi:10.1080/14759390902992576.
- Kirkwood, A., & Price, L. (2005). Learners and learning in the twenty-first century: What do we know about students' attitudes towards and experiences of information and communication technologies that will help us design courses? *Studies in Higher Education*, 30(3), 257–274. doi:10.1080/03075070500095689.
- Krishankumar, R., Nimmagadda, S. S., Rani, P., Mishra, A. R., Ravichandran, K. S., & Gandami, A. H. (2021). Solving renewable energy source selection problems using a q-rung orthopair fuzzy-based integrated decision-making approach. *Journal of Cleaner Production*, 279, 123329. doi:10.1016/j.jclepro.2020.123329.
- Kuhn, C., & Lucke, D. (2021). Supporting the digital transformation: A low-threshold approach for manufacturing related higher education and employee training. *Procedia CIRP*, 104, 647–652. doi:10.1016/j.procir.2021.11.109.
- Liu, P., Rani, P., & Mishra, A. R. (2021). A novel Pythagorean fuzzy combined compromise solution framework for the assessment of medical waste treatment technology. *Journal of Cleaner Production*, 292, 126047. doi:10.1016/j.jclepro.2021.126047.
- Liu, P., & Wang, P. (2018). Some q-Rung orthopair fuzzy aggregation operators and their applications to multiple-attribute decision making. *International Journal of Intelligent Systems*, 33(2), 259–280. doi:10.1002/int.21927.
- Mahlow, C., & Hediger, A. (2019). Digital transformation in higher education—buzzword or opportunity? *eLearn*, 2019(5). doi:10.1145/3329488/3331171 Article 13.
- Majid, M., Habib, S., Javed, A. R., Rizwan, M., Srivastava, G., Gadekallu, T. R., et al. (2022). Applications of wireless sensor networks and internet of things frameworks in the industry revolution 4.0: A systematic literature review. *Sensors*, 22, 2087. doi:10.3390/s22062087.
- Marcelo, C., & Yot-Domínguez, C. (2019). From chalk to keyboard in higher education classrooms: Changes and coherence when integrating technological knowledge into pedagogical content knowledge. *Journal of Further and Higher Education*, 43(7), 975–988. doi:10.1080/0309877X.2018.1429584.
- Margaryan, A., Littlejohn, A., & Vojt, G. (2011). Are digital natives a myth or reality? University students' use of digital technologies. *Computers & Education*, 56(2), 429–440. doi:10.1016/j.compedu.2010.09.004.
- Matt, C., Hess, T., Benlian, A., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, 15(2), 6.
- McCusker, C., & Babington, D. (2015). *The 2018 digital university: Staying relevant in the digital age*. [www.pwc.co.uk/2018university](http://www.pwc.co.uk/2018university).
- McGovern, E., Moreira, G., & Luna-Nevez, C. (2020). An application of virtual reality in education: Can this technology enhance the quality of students' learning experience? *Journal of Education for Business*, 95(7), 490–496. doi:10.1080/08832323.2019.1703096.
- Mishra, A. R., & Rani, P. (2021). A q-rung orthopair fuzzy ARAS method based on entropy and discrimination measures: An application of sustainable recycling partner selection. *Journal of Ambient Intelligence and Humanized Computing*. doi:10.1007/s12652-021-03549-3.
- Newman, T., & Beetham, H. (2017). *Student digital experience tracker 2017: The voice of 22,000 UK learners*. Bristol: Jisc.
- Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education*, 59(3), 1065–1078. doi:10.1016/j.compedu.2012.04.016.
- Núñez-Canal, M., de Obeso, M. D. I. M., & Pérez-Rivero, C. A. (2022). New challenges in higher education: A study of the digital competence of educators in Covid times. *Technological Forecasting and Social Change*, 174, 121270. doi:10.1016/j.techfor.2021.121270.
- OECD. (2015). *Schooling redesigned*. doi:10.1787/9789264245914-en.
- OECD. (2015). *Students, computers and learning*. doi:10.1787/9789264239555-en.

- Oliveira, K. K.d. S., & de Souza, R. A. C. (2021). Digital transformation towards education 4.0. *Informatics in Education*. doi:10.15388/infedu.2022.13.
- Oliver, B., & Jorre de St Jorre, T. (2018). Graduate attributes for 2020 and beyond: Recommendations for Australian higher education providers. *Higher Education Research & Development*, 37(4), 821–836. doi:10.1080/07294360.2018.1446415.
- Pensel, S., & Hoffhues, S. (2017). Digitale Lerninfrastrukturen an Hochschulen. Systematisches Review zu den Rahmenbedingungen für das Lehren und Lernen mit Medien an deutschen Hochschulen.
- Petrova, N., & Bondareva, G. (2019). Digitalization and digital technologies in education. *World of Science Culture and Education*, 5(78), 354.
- Pham, H., Tran, Q. N., La, G. L., Doan, H. M., & Vu, T. D. (2021). Readiness for digital transformation of higher education in the Covid-19 context: The dataset of Vietnam's students. *Data in Brief*, 39, 107482. doi:10.1016/j.dib.2021.107482.
- Rani, P., & Mishra, A. R. (2020). Multi-criteria weighted aggregated sum product assessment framework for fuel technology selection using q-rung orthopair fuzzy sets. *Sustainable Production and Consumption*, 24, 90–104. doi:10.1016/j.spc.2020.06.015.
- Rani, P., Mishra, A. R., Krishankumar, R., Ravichandran, K. S., & Gandomi, A. H. (2020). A new pythagorean fuzzy based decision framework for assessing healthcare waste treatment. *IEEE Transactions on Engineering Management*, 1–15. doi:10.1109/TEM.2020.3023707.
- Rodrigues, L. S. (2017). Challenges of digital transformation in higher education institutions: A brief discussion. In *Proceedings of the 30th international business information management association conference, IBIMA 2017 Vision 2020: Sustainable economic development, innovation management, and global growth*.
- Rof, A., Bikfalvi, A., & Marques, P. (2022). Pandemic-accelerated digital transformation of a born digital higher education institution towards a customized multimode learning strategy. *Educational Technology & Society*, 25(1), 124–141. <https://www.jstor.org/stable/48647035>.
- Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). *Diffusion of innovations*. Routledge.
- Sanz, R., Peris, J. A., & Escámez, J. (2017). Higher education in the fight against poverty from the capabilities approach: The case of Spain. *Journal of Innovation & Knowledge*, 2(2), 53–66. doi:10.1016/j.jik.2017.03.002.
- Shrivastava, A. (2018). Using connectivism theory and technology for knowledge creation in cross-cultural communication. *Research in Learning Technology*, 26(0). doi:10.25304/rlt.v26.2061.
- Skare, M., & Riberio Soriano, D. (2021). How globalization is changing digital technology adoption: An international perspective. *Journal of Innovation & Knowledge*, 6(4), 222–233. doi:10.1016/j.jik.2021.04.001.
- Sullivan, C., & Staib, A. (2018). Digital disruption 'syndromes' in a hospital: Important considerations for the quality and safety of patient care during rapid digital transformation. *Australian Health Review*, 42(3), 294–298. doi:10.1071/AH16294.
- Tamim, R. M., Bernard, R. M., Borokhovski, E., Abrami, P. C., & Schmid, R. F. (2011). What forty years of research says about the impact of technology on learning: A second-order meta-analysis and validation study. *Review of Educational Research*, 81(1), 4–28. doi:10.3102/0034654310393361.
- Tatar, D., Roschelle, J., Knudsen, J., Shechtman, N., Kaput, J., & Hopkins, B. (2008). Scaling up innovative technology-based mathematics. *Journal of the Learning Sciences*, 17(2), 248–286. doi:10.1080/10508400801986090.
- Welsh, D. H. B., Tullar, W. L., & Nemati, H. (2016). Entrepreneurship education: Process, method, or both? *Journal of Innovation & Knowledge*, 1(3), 125–132. doi:10.1016/j.jik.2016.01.005.
- Williams, M., Burden, R., & Lanvers, U. (2002). 'French is the language of love and stuff': Student perceptions of issues related to motivation in learning a foreign language. *British Educational Research Journal*, 28(4), 503–528. doi:10.1080/0141192022000005805.
- Windasari, N. A., Kusumawati, N., Larasati, N., & Amelia, R. P. (2022). Digital-only banking experience: Insights from gen Y and gen Z. *Journal of Innovation & Knowledge*, 7(2) 100170. doi:10.1016/j.jik.2022.100170.
- Yager, R. R. (2017). Generalized orthopair fuzzy sets. *IEEE Transactions On Fuzzy Systems*, 25(5), 1222–1230. doi:10.1109/TFUZZ.2016.2604005.
- Yazdani, M., Zarate, P., Kazimieras Zavadskas, E., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision*, 57(9), 2501–2519. doi:10.1108/MD-05-2017-0458.
- Zaritsky, R., Kelly, A. E., Flowers, W., Rogers, E., & O'Neill, P. (2003). Clinical design sciences: A view from sister design efforts. *Educational Researcher*, 32(1), 32–34. doi:10.3102/0013189X032001032.
- Zhang, J., Zhang, X., Liu, W., Ji, M., & Mishra, A. R. (2022). Critical success factors of blockchain technology to implement the sustainable supply chain using an extended decision-making approach. *Technological Forecasting and Social Change*, 182, 121881. doi:10.1016/j.techfore.2022.121881.