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Technological Acceptance of Industry 4.0 by Students from Rural Areas

Mauricio Castillo-Vergara [1,*], Alejandro Álvarez-Marín [2], Eduardo Villavicencio Pinto [3,4] and Luis Enrique Valdez-Juárez [5]

1 Facultad de Economía y Negocios, Universidad Alberto Hurtado, Santiago 8320000, Chile
2 Departamento de Ingeniería Industrial, Universidad de La Serena, La Serena 1720170, Chile; aalvarez@userena.cl
3 PROCASUR NGO, Heriberto Covarrubias 21, Oficina 705 Ñuñoa, Santiago 7750000, Chile; eavillavicencio@uc.cl
4 Dirección de Formación Continua, Universidad SEK, Fernando Manterola 0789, Santiago 7520317, Chile
5 Department of Business and Economics Sciences, Technological Institute of Sonora Mexico, Obgregon 85000, Mexico; levaldez@itson.edu.mx
* Correspondence: mhcastillo@uahurtado.cl

Abstract: In this study, our objective was to identify the factors that explain the acceptance of Industry 4.0 technologies by technical students. Industry 4.0 is made up of a series of technologies, such as the Internet of Things; cyber-physical systems; big data, data analytics, or data mining; cloud computing or the cloud; augmented reality or mixed reality; additive manufacturing or 3D printing; cybersecurity; collaborative robots; artificial intelligence; 3D simulation; digital twin or digital twin; drones. We designed a theoretical model based on the technology acceptance model to explain the acceptance of these technologies. The study was carried out on a sample of 326 technical professional students. Students are considered ideal samples to test theoretical predictions regarding the relationships between variables in emerging technologies. The results show the positive effect of technological optimism on perceived usefulness and ease of use. However, there was not a direct effect on the attitude towards the use. A mediating effect was established. In addition, the facilitating conditions influence optimism and the ease of using the technology. These elements influence the attitude and intention to use, which is consistent with previous studies on technology acceptance. The results will guide the design of public policies to incorporate technologies into education.

Keywords: Industry 4.0; technology; technology acceptance model; emerging technologies

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1. Introduction

The future of rural development has aroused the interest of broad and diverse academic communities, which is due, among other things, to its relevance when facing the effects of massive shocks, such as the COVID-19 pandemic or the sustained increase in food prices [1–3]. An essential point on the global research agenda has been the inclusion of 4.0 technologies in agriculture, looking at both their social and environmental impacts [4], the effects on transition patterns [5], and the types of challenges they may face [6], such as the construction of territorial indicators [7], or their practical implementation in production [8]. However, there does not seem to be a sufficient approximation regarding the degree of acceptance between this technological phenomenon and a whole social group for the future of agricultural development, such as rural youth.

With regard to this group, in particular, the literature discusses, at a theoretical level, the possibility of sharing a definition that addresses the diversity of conditions and characteristics that rural youth represent [9–11], the factors that influence the development of their economic activities [12,13], and the elements that affect national and international mobility practices [14,15].

Although during the last decade of the 20th century, there was little theoretical evolution in the study of rural youth [14,16], some factors made it possible for this context to markedly change, intensifying structural analysis within the framework of public policy design. Thus, during the last five years, the difficulties, challenges, and opportunities faced by rural youth have been at the center of the concerns of both governments and international organizations linked to rural development. The International Fund for Agricultural Development (IFAD), in its 2019 annual report, highlights the depth of the economic and technological transformations that this group is experiencing worldwide. This preoccupation has generated high expectations and uncertainty about which methods would be more efficient in improving their living conditions [17].

The report states that there are three essential elements for the development of rural youth. Increased productivity is associated with the challenge of improving educational conditions to facilitate interaction with technological schemes that have a positive impact on the efficiency of economic processes; connectivity has the potential to create more opportunities to generate business [18]; finally, agency refers to rural youth's ability to make autonomous and empowered decisions about their life strategies. In turn, access to better information and education has increased financial and labor expectations, which has strained the ecosystem of opportunities offered by rural areas, which are characterized by a diversity of structural conditions [19].

In addition to the above, rural young people's aspirations or ways of perceiving the future have played a central role in their interaction with technology and the type of strategic decisions that they make. This trajectory could be mediated by global factors, such as the climate crisis, but also by the local adaptive capacity of agriculture in the face of economic phenomena, which are dominated by growing and dominant corporate and industrial participation, for example, in the area of food production [20].

Following the criteria used by the National Youth Institute of Chile and the Ibero-American Youth Organization, rural youth are defined as the population between 15 and 29 years of age who live in rural areas, which represents 13% of people at the national level. Regarding their socio-labor characteristics, the essential occupational sectors are agriculture (37%), commerce (17%), and services (16%). This group's education level is significantly higher than that of their parents due to the universalization and increased territorial coverage of the Chilean educational system, which has allowed them to become, among other things, stable and recurrent users of technologies. Although rural youth, in general, have access to low-skilled jobs, there is an essential group of young people with expectations linked to agricultural innovation. They believe that access to technologies, investments, and credit systems is necessary for this [14].

Industry 4.0 (I4.0) represents a recent technology trend [21,22]. This is a significant revolution that is changing industry, as well as social and economic life [23]. It is based on the adoption of digital technologies [24–26] for the collection of data in real time, which provide helpful information to systems [27,28]. I4.0 is based on several technological pillars (big data, cloud, industrial internet, horizontal and vertical integration, simulation, augmented reality, additive manufacturing, cybersecurity, and advanced manufacturing) [29,30]. The key benefits of I4.0 reported in the literature include: cost reduction; improvements in quality, efficiency, flexibility, and productivity; and a competitive advantage [31]. What could be used as a springboard for the development of rural youth?

With the advancement of this technology and its incorporation into both professional and private user environments, whether it is accepted or rejected is critical. Leveraging I4.0 technologies is far from trivial, and user acceptance is key to successfully implementing the technology [32]. Since I4.0 relies heavily on interactions between individuals, technologies, organizations, and people, it is critical to investigate the causal factors for adopting and using the technology [33]. The Technology Acceptance Model (TAM) has evolved to become the crucial model in understanding the predictors of human behavior towards potential technology acceptance or rejection [34], has been widely used to recognize the factors that affect technology acceptance in a variety of contexts [35,36], and is considered an influential model that is commonly applied in the field of information systems [37]. Therefore, given that the TAM model is among the most widely used for modeling behaviors, we find it helpful when modeling the intention to adopt Industry 4.0 technologies by technical professional students from rural areas.

The I4.0 acceptance study has been addressed in other contexts, such as small and medium enterprises [31], manufacturing companies [38], managers [32], and governments [39]. However, to the best of our knowledge, it has not been addressed from the students' perspectives. This situation is serious because investments in any new technology are costly and require a lot of time and effort [40], and future professionals could affect the success of these initiatives.

Therefore, this study aimed to measure the acceptance of Industry 4.0 technology in vocational–technical studies and, additionally, to address the call to extend the original TAM by incorporating new variables to improve its applicability and validity [33,34,41]. We have introduced subjective norms, enabling conditions, and technological optimism as the factors that could explain technology acceptance.

The remainder of the paper is structured as follows. The theoretical foundations and hypotheses are presented. Then, the methodology and results are presented. Finally, a discussion of the results and the conclusions of the study are presented.

2. Theoretical Background and Hypotheses

In 1985, Davis [42] proposed the technology acceptance model (TAM) as an adaptation of the theory of reasoned action (TRA), which was initially proposed by [43] to specifically explain computer-usage behavior. The TRA demonstrates the intention to use through attitudes towards using and subjective norms. However, the TAM suggests that the subjective criteria do not directly influence attitudes towards use. Attitudes towards using and use could be explained by perceived ease of use and perceived usefulness. Two additional extensions to the models have also been proposed: TAM2 [44] and TAM3 [45], both of which include other factors, such as subjective norms, that contribute to a better explanation of the intention of use [46].

Parasuraman [47] proposed the construct of technology readiness (TR) to explain technological acceptance. This is composed of four dimensions: optimism and innovativeness, as drivers of technology readiness, as well as discomfort and insecurity, which are inhibitors. However, previous studies suggest that optimism and innovativeness are stable individual dimensions used to measure TR [48].

Venkatesh et al. proposed [49] the unified theory of acceptance and use of technology (UTAUT), and, in 2012, an extension of this (UTAUT2) [50], with the purpose of integrating various existing models. In both cases, social influence is proposed as one of the constructs that helps to explain the behavioral intention to use.

Lin, Shih, and Sheren proposed the TRAM model [51], which uses TR as a construct in the TAM model, thus explaining its influence on perceived ease of use and perceived usefulness, as well as behavioral intention to use.

However, the TAM model proposed by Davis is widely used to study the adoption of new technologies [52]. This model explains the factors that could lead a user to adopt a certain technology [53], and it considers the impact of these factors on the attitude towards use and, finally, on the intention to use [54]. This model comprises several variables that directly or indirectly explain behavioral intentions and technology use (i.e., perceived usefulness, perceived ease of use, attitudes towards technology) and it can be extended with external variables, such as self-efficacy, subjective norms, and the facilitating conditions of technology use [40].

Numerous studies confirm the robustness of the model, emphasizing its broad applicability to a diverse set of technologies and users [30]. It has been used in recent years to study the adoption of new technologies, such as wearables [55], Google Glass [56], augmented reality [57], Smart Home systems [58], IoT-based systems [24], and digital transformation strategies [59].

Based on the above, a theoretical model was developed using the TAM to understand Industry 4.0 acceptance.

Facilitating Conditions

Enabling conditions are defined as the degree to which an individual perceives that an organizational and technical infrastructure exists to support the use of a technology [60]. Individuals who are unfamiliar with new technologies may have difficulty using them. However, if they have sufficient contextual support, they can easily accept the technology [61]. Then, the facilitating conditions consist of modifying objective factors that support the easy use of the technology [62]. The presence of favorable conditions, such as internet availability, technological support, organizational/managerial support, motivation, etc., can enhance people's willingness to try new technologies [63]. Facilitating conditions are the perceived enablers or barriers in the environment that influence a person's perception of the ease or difficulty of performing a task [64]. These serve as a critical indicator for the promotion of new technology because they help users learn to use the technology within a shorter period, and minimize the problems that they may encounter when using it [65]. In addition, facilitating conditions regarding the use of software have been related to technological optimism [66]. Based on these antecedents, we propose the following hypotheses:

Hypothesis 1 (H1). *Facilitating conditions will be significantly associated with technological optimism.*

Hypothesis 2 (H2). *Facilitating conditions will be significantly associated with ease of use.*

Subjective Norms

The subjective norm refers to the perception of people importance to an individual regarding a specific behavior [43]. The importance of people's opinions to an individual can influence the use of technologies [67].

In a systematic review of 142 studies in the banking sector, the influence of subjective norms on the perceived usefulness of using banking-service applications was determined [68]. Industry 4.0 is characterized by an increase in the digitization of its operations [69]. One of the technologies that led the digitization processes in this industry is augmented reality. The influence of subjective norms on the intention to use AR applications has been studied [70] with regard to their perceived usefulness [71,72]. Therefore, we formulated the following hypothesis:

Hypothesis 3 (H3). *Subjective norms will be significantly associated with perceived usefulness.*

Technological Optimism

Technological optimism is defined as "a positive view of technology and the belief that it offers people increased control, flexibility, and efficiency in their lives" [47]. It is associated with a positive view of technology and with the belief that it can increase control, flexibility, and efficiency in life [73]. Therefore, people who are optimistic about using new technologies are believed to have positive intentions to use them. They consider technology helpful and are not concerned about its negative outcomes [74]. As a result, optimists are more willing to use new technologies and knowledge [75]. Today's students are considered digital natives, and most of them have favorable views towards the use of technology [76]. Technological optimism is a strong predictor of technology choice in some young people compared with adults [77] (for example, in new learning methods [73], the adoption of mobile banking [74], or cryptocurrencies [78]). This view shows their tendency to be pioneers in using technology as a motivational behavior [79], and a positive relationship between technological optimism and perceived ease of use and perceived usefulness [80]. With these arguments, we put forward the following hypotheses:

Hypothesis 4 (H4). *Technological optimism will be significantly associated with perceived usefulness.*

Hypothesis 5 (H5). *Technological optimism will be significantly associated with attitude towards use.*

Hypothesis 6 (H6). *Technological optimism will be significantly associated with perceived ease of use.*

Technology Acceptance Model

There is sufficient support [41,42,57,81,82] for the role of perceived usefulness (PU), which is understood as "the degree to which a person believes that using a particular system would improve performance." Perceived ease of use (PEOU) is defined as "the degree to which a person believes that using a particular system would be effortless", which is a significant factor in predicting variations in the attitude towards technology use. Davis [42] defines attitudes towards new system use (ATU) as "an individual's general effective reaction to the use of the system," and perceived ease of use (PEOU) has been explained as "the degree to which an individual believes that he or she will continue to use the system." Considering the TAM model, we consider the following hypotheses:

Hypothesis 7 (H7). *Perceived usefulness will be significantly associated with attitude towards use.*

Hypothesis 8 (H8). *Perceived ease of use will be significantly associated with attitude towards use.*

Hypothesis 9 (H9). *A positive attitude towards technology use will be significantly associated with intention to use.*

Figure 1 presents the proposed research model.

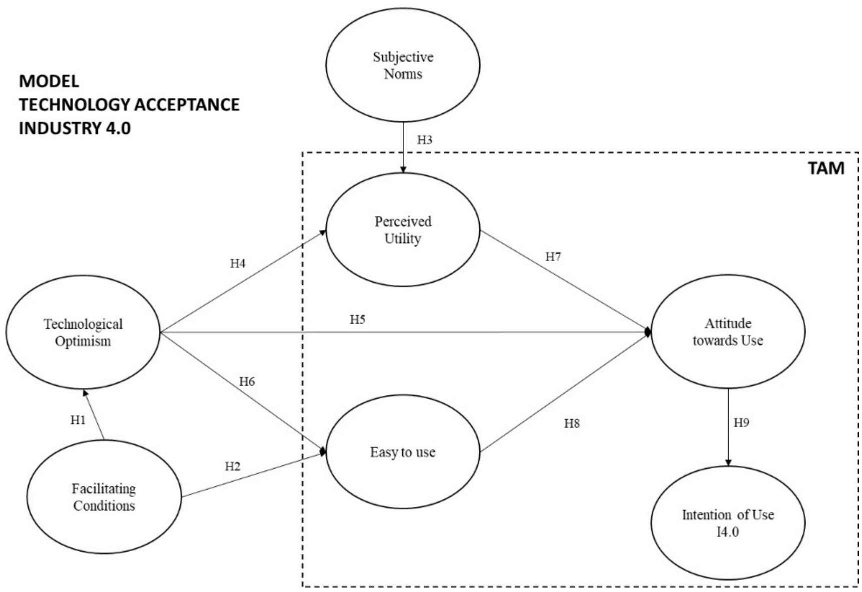

Figure 1. Research model.

3. Methodology

Data were analyzed using structural equation modeling (SEM), based on variance, taking advantage of the partial-least-squares (PLS) technique, which is suitable for information processing in social science research and has advantages over SEM and traditional multivariate analysis [83]. Structural equation modeling is implemented in research that seeks to test complex models [84]. Two models have been calculated using this technique: the measurement model (or external), which relates the observed variables to the latent variables, and the structural model (or internal), which calculates the strength and direction of the relationships between the variables [85]. The steps differ depending on whether the measurement model is reflective or formative. In this case, for reflective measurement models, the steps are as follows: (1) estimate the item loads and assess the importance; (2) assess the reliability of the indicator; (3) assess the overall reliability constructs; (4) examine the average variance extracted (AVE); (5) confirm the discriminant validity using the HTMT method; (6) assess the nomological validity [86].

Empirical Context and Data Sources

The sample comprised 326 students within technical–professional education. Students are considered ideal samples for testing theoretical predictions regarding variable relationships [87], which is in line with this study. Student samples have frequently been used in exploratory technology-adoption studies [29]. Information was obtained from a self-administered questionnaire following participation in a workshop on Industry 4.0. Indications were given that there were no right or wrong answers, and the anonymity and strict confidentiality of the data were guaranteed.

The survey was applied between the months of May and June 2021. A total of 37% of the interviewees were women, and 63% were men. The average age was 19 years, and the median was 18 years, with a minimum age of 15 years and a maximum of 30 years.

Measures

The scale was elaborated from the literature review and previous studies. Table 1 presents the indicators associated with the model constructs.

Table 1. Studies and indicators used.

Construct	Study	Indicator
Subjective norms	[88]	People whose opinions I value encourage me to use new Industry 4.0 technologies. People who are important to me help me use the new Industry 4.0 technologies.
Technology optimism	[89]	The products and services that use the newest technologies are much more convenient. I prefer to use the most advanced technology available. Technology makes my work more efficient.
Facilitating conditions	[90]	I can easily access information on how to use Industry 4.0 technology. Industry 4.0 technology is compatible with other technologies I use (tablet, notebook, smartphone). I can easily get guidance and instruction if I have difficulties in using Industry 4.0 technologies.
Perceived ease of use	[91]	The use of Industry 4.0 technologies is easy for me. The use of Industry 4.0 technologies is understandable and clear to me. It will not be difficult for me to be proficient in the use of Industry 4.0 technologies.
Perceived usefulness	[92]	Industry 4.0 technology can help me to be more efficient. Industry 4.0 technology is useful. The use of Industry 4.0 technologies benefits me
Attitude towards using	[91]	The use of Industry 4.0 technologies is a good idea. The use of Industry 4.0 technologies is a wise idea. I like to develop my activities using Industry 4.0 technologies.
Behavioral intention to use	[93]	I intend to use Industry 4.0 technologies in the coming months. I will continuously use Industry 4.0 technologies in my activities. In general, I am willing to use Industry 4.0 technologies for the development of my activities. I would recommend others to incorporate Industry 4.0 technologies in their activities.

Data Analysis

The hypotheses were tested using the Smart PLS 3.3.9 © package [94] and partial least squares. The technique consists of different steps and has been previously used in this type of exploration [95]. First, the model fitting is performed by applying a bootstrapping process (5000 subsamples). Second, the measurement model is evaluated [96], which is followed by an evaluation of the structural model [97].

4. Results

The study had 326 participants, of whom 63% were male and 37% were female. The average age was 19 years, and the students were in their third or fourth academic year. Of those interviewed, 27% were studying and working, 67% were only studying, and the rest shared their studies with unpaid work. Regarding technical specialization, the sample showed that 16% were students of automotive mechanics, 20% were agricultural technical students, 56% were agricultural technical students, and 8% were technical students in agroindustrial and agricultural administration.

The loading (λ) of each item is more significant than 0.707, which verifies the reliability of the indicator [98]. The reliability of the construct was satisfied if it had values greater than 0.7 for the Cronbach's alpha coefficients, composite reliability, and Dijkstra–Henseler indicator (RhoA) [99], as presented in Table 2. The convergent validity is presented in Table 3, of which the values are higher than 0.5 [100]. Table 4 also shows the heterotrait–monotrait ratios (HTMT) with values below 1, which provide discriminant validity evidence [97].

Table 2. Evaluation of the measurement model.

Construct/Indicator	Loads	Cronbach's Alpha	Dijkstra–Henseler's Rho	Composite Reliabilities	Average Variance Extracted
Subjective norm (SN)		0.8391	1.201	0.9168	0.8468
SN1	0.8657				
SN2	0.9716				
Technology optimism (TO)		0.9029	1.116	0.9283	0.8126
TO1	0.9619				
TO2	0.9244				
TO3	0.8113				
Facilitating conditions (FC)		0.8994	1.056	0.9324	0.8217
FC1	0.9300				
FC2	0.9352				
FC3	0.8518				
Perceived ease of use (PEOU)		0.8971	0.913	0.9353	0.8282
PEOU1	0.8958				
PEOU2	0.9371				
PEOU3	0.8966				
Perceived usefulness (PU)		0.9321	1.558	0.9474	0.8574
PU1	0.9048				
PU2	0.9721				
PU3	0.8992				
Attitude towards using (ATU)		0.9305	1.185	0.952	0.8688
ATU1	0.8948				
ATU2	0.9758				
ATU3	0.9239				
Behavioral intention to use (BIU)		0.9177	1.034	0.9354	0.7838
BIU1	0.8976				
BIU2	0.8124				
BIU3	0.9017				
BIU4	0.9255				

Table 3. Fornell–Larcker criterion.

	ATU	BIU	PEOU	PU	SN	FC	TO
ATU	0.9321						
BIU	0.8731	0.8853					
PEOU	0.8220	0.8055	0.9100				
PU	0.8501	0.8204	0.7256	0.9260			
SN	0.7463	0.7364	0.7405	0.6510	0.9202		
FC	0.7204	0.7427	0.7675	0.6417	0.7036	0.9065	
TO	0.7477	0.7449	0.7390	0,.3910	0.6629	0.7570	0.9015

Note: ATU: attitude towards using; BIU: behavioral intention to use; PEOU: perceived ease of use; PU: perceived usefulness; S.N.: subjective norm; FC: is facilitating conditions; TO: technology optimism.

Table 4. Heterotrait–Monotrait ratios.

	ATU	BIU	PEOU	PU	SN	FC	TO
ATU							
BIU	0.9223						
PEOU	0.8961	0.9032					
PU	0.8933	0.8804	0.7947				
SN	0.8231	0.8244	0.8585	0.7261			
FC	0.7736	0.8041	0.8632	0.6772	0.8039		
TO	0.7875	0.8072	0.7891	0.8038	0.7377	0.7976	

Note: ATU: attitude towards using; BIU: behavioral intention to use; PEOU: perceived ease of use; PU: perceived usefulness; SN: subjective norm; FC: facilitating conditions; TO: technology optimism.

The results obtained for the model are presented in Table 5 and illustrated in Figure 2. Eight hypotheses are accepted, and one is rejected. The results are consistent with those of other studies that capture the predictive power of the TAM in the educational environment. The R2 values represented in the figure are significant at 0.01%; all values meet the minimum requirements [101,102].

Table 5. Results from the structural model.

Hypothesis	Path	*t*-Value	*p*-Value	Supported
H1: *Facilitating Conditions (FC)→Technology optimism (TO)*	0.7570	12.519	0.0000	Yes
H2: *Facilitating Conditions (FC)→Perceived ease of use (PEOU)*	0.4873	4.229	0.0000	Yes
H3: *Subjective norm (SN)→Perceived usefulness (PU)*	0.2874	2.563	0.0052	Yes
H4: *Technology optimism (TO)→Perceived usefulness* (PU)	0.5486	4.378	0.0000	Yes
H5: *Technology optimism (TO)→Attitude towards using (ATU)*	0.0860	0.793	0.2139	No
H6: *Technology optimism (TO)→Perceived ease of use (PEOU)*	0.3703	3.071	0.0011	Yes
H7: *Perceived usefulness* (PU)*→Attitude towards using (ATU)*	0.4989	4.072	0.0000	Yes
H8: *Perceived ease of use (PEOU)→Attitude towards using (ATU)*	0.3965	3.327	0.0004	Yes
H9: *Attitude towards using (ATU)→Behavioral intention to use (BIU)*	0.8731	32.785	0.0000	Yes

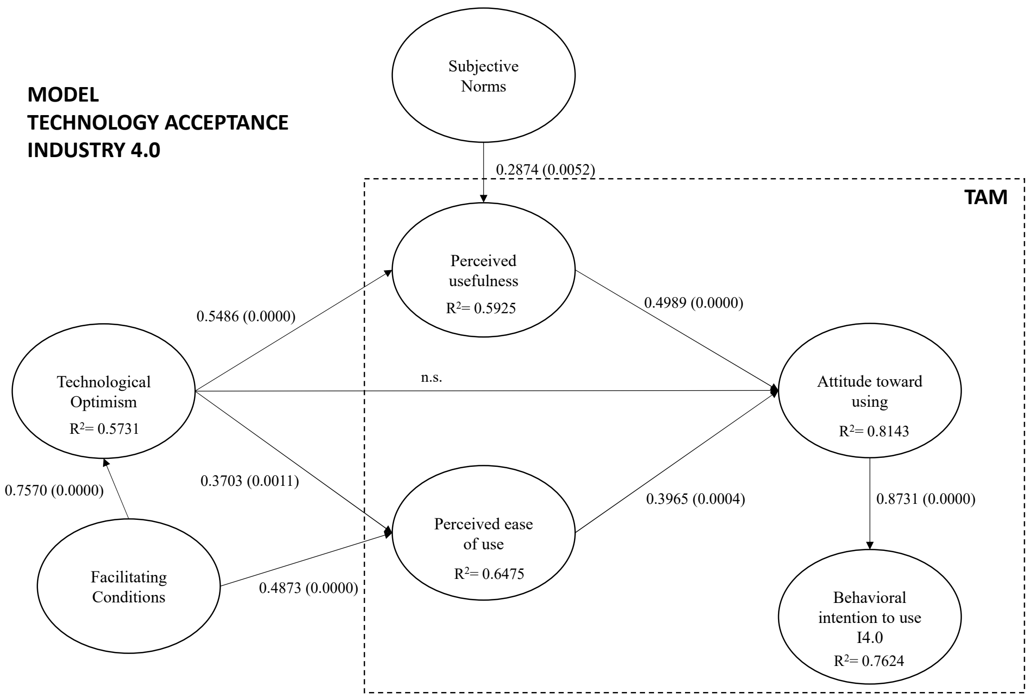

Figure 2. Resulting research model. Dashed arrow shows nonsignificant paths.

5. Discussion

This section discusses the study's main findings in the order in which the model hypotheses are presented. A theoretical model was developed, using the TAM, to understand

Industry 4.0 acceptance, based on previous research. The results show that the acceptance of H1 and H2, and the enabling conditions, which are defined as the degree to which an individual perceives that an organizational and technical infrastructure exists to support the use of the system, will positively affect technological optimism and perceived ease of use [60]. Regarding technological optimism, favorable conditions generate a propensity to try new technologies and are established as an indicator to promote the use of new technology [63], helping users use the technology sooner and reducing problems in its use [65]. If there is sufficient support, even people who may have difficulties using the technology may perceive greater ease. Recently, countries with emerging economies in rural areas of Latin America are betting on investment in technological infrastructure to trigger innovation and thereby reinforce the resilience of societies and sustain the economy in the face of global megatrends, such as demographic, technological, and environmental changes during the current global crisis caused by the COVID-19 pandemic [103].

Subjective norms have been widely considered in many models that have traditionally been used to assess technology adoption, and they refer to the "perceived pressures on a person to perform a given behavior and the person's motivation to comply with those pressures" [104]. H3 is accepted, showing that subjective norms influence how the student is affected by the perceptions of some significant referents (family, friends, teachers) regarding the perceived usefulness of I4.0. The results are in line with other studies and technologies [105], and it is suggested that subjective norms have an indirect effect on the intention to use through perceived usefulness, as is the case in this study [106]. Starting from the perspective of the TAM model developed by Davis in 1989, subjective norms are not the most determining factor for the use of technologies and their adaptability. Therefore, people's intrinsic and extrinsic behavioral factors are complementary and influence technology adoption [107]. These manifestations occur in individuals in educational and business contexts.

Technological optimism does not directly affect the decision to use or reject H5. Its effect is mediated by the variable's usefulness and ease of use, meaning that H4 and H6 are accepted. When people are more innovative, they can withstand a higher degree of uncertainty and have more positive intentions to use the innovation. In other words, they are less likely to perceive risks and are more receptive to technological innovation [108], thus perceiving greater usefulness and ease of use. This optimistic view of technology makes them more inclined to see the positives of the adoption process. However, technological optimism is often clouded by external factors from the social, economic, and cultural environments. During the COVID-19 pandemic, people (young people and adults) experienced unprecedented emotional impacts, which led to stress and high resistance to the use of unfamiliar digital platforms [109]. Therefore, mistrust in technologies increased in urban communities and was more accentuated in rural populations [110].

Our results for H7, H8, and H9 are in line with previous research on the roles of perceived usefulness (PU), which is understood as "the degree to which a person believes that using a particular system would improve his or her performance", and perceived ease of use (PEOU), which is defined as "the degree to which a person believes that using a particular system would be effortless", as significant factors in predicting variations in the attitude towards using I4.0 technologies. In addition, the more favorable the students' attitudes towards I4.0 use, the greater their intentions to use the technology [42]. Although there is a significant digital divide between urban and rural areas in the Latin American region, the adoption of Industry 4.0 is becoming more pervasive in different economic sectors. In education, new technologies have promoted new forms of learning through digital platforms, which can educate at a distance and in real time [111]. Therefore, the academic society shows high perceived usefulness and a positive attitude regarding the use of increasingly intelligent and autonomous technology [112].

Regarding the R^2 values, the results of attitude towards use (81.43%) and intention to use (76.24%) are sufficiently high to explain the endogenous variables. For the other variables, the result is considered moderate [96,102].

6. Conclusions

In this study, we proposed an extended TAM model to explore the factors that may influence technical education students' intention to use Industry 4.0 technology. Several studies have addressed the acceptance of these technologies. However, none have considered the educational field that we have addressed in this study. Therefore, our study has high theoretical value and contributes to the development and strengthening of the TAM model by exploring the internal and external factors that affect the behavior and use of new technologies through Industry 4.0.

We have also introduced an external variable to the model, which is referred to as technological optimism, to understand its influence on attitudes towards using technology, considering that this population is regarded as digital natives. Considering this condition, educational institutions and public policymakers should consider this characteristic as a strength. Students can be introduced to technology and challenged to incorporate it into their educational processes. Agile methodologies of entrepreneurship and innovation should be introduced so that students use technology to solve problems. This strengthens students' creative abilities. Indeed, future work activities will require these capabilities with the imminent arrival of I4.0. The rural regions of Latin American countries face more significant challenges than these communities or areas in countries with more stable economies. Therefore, our study makes an empirical contribution of high value by exploring the particularities that make up the TAM model when applied to behavior and application in student communities.

The inclusion of subjective norms is also fascinating, as it helps us to understand how the environment can influence the usefulness of this technology. We believe that teachers' perceptions of these technologies can affect the students' perceived usefulness. Previous studies in this segment show the importance of the teacher's role in the professional expectations of students, and mainly in lower-income groups [96]. In addition, student communities have been making greater use of new technologies in the current hectic times caused by the COVID-19 pandemic. This has converted the regions into digital and virtual communities to improve education and culture and strengthen the economy [110,113].

Training can be supplied to address the integration of technology into the educational process to support this outcome. For example, augmented-reality or virtual-reality applications allow for integrating teaching. Alternatively, programs can be promoted that support the creation of technology startups that develop technology for incorporation into the classroom. Given the importance of the subjective norms, it is recommended that educational institutions support these processes and do not leave this task to the trainers.

These recommendations are intended to strengthen the virtual educational models applied in rural communities through the use of Industry 4.0 [114]. During the COVID-19 pandemic, most citizens from different regions, including students, showed greater resilience when adapting to new technological changes, as well as the actions that helped them in terms of struggles and survival [115].

In addition to the practical implications described above, the present study has several theoretical implications. First, we propose an extended TAM model to explore the factors that influence students to use technologies associated with I4.0. The proposed model adds value because, although many studies have addressed technological acceptance in education, we have not found studies that relate it to the field addressed. However, several studies analyze I4.0 in education. Still, the focus is on the skills required by students, the integration of I4.0 into curricula, and the effectiveness of teaching technologies. However, the acceptance of the technology by the users is critical; otherwise, the institutions' efforts may be unsuccessful. Secondly, we incorporate factors that have not been studied in this context, such as technological optimism and facilitating conditions. With this, we hope to understand the behavior of students exposed to new technologies that are incorporated into the world of work. Finally, this study validates the results generated from the TAM model for technology acceptance and use. In doing so, we extend the theoretical model to a field that has not been addressed.

The work is not free of limitations, which may lead to future lines of research. First, the sample refers to technical students, and so the results cannot be generalized. Future work could include other students or professionals. Secondly, the information is cross-sectional; future research could consider longitudinal studies that allow for a longer-term view or other techniques [116,117]. Other lines of research that could be addressed from our study include models that explain which factors facilitate I4.0 adoption in emerging-market SMEs, what kinds of resources and capabilities affect the implementation of I4.0, or the impact of I4.0 on performance and innovation. Finally, innovation ecosystems could be developed to boost startups using I4.0 as a value proposition.

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