Students' Entrepreneurial Orientation in Italy: do digital and coding skills matter?

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Abstract

The literature presents several papers regarding students' entrepreneurial intention. However, only a few papers have recently analyzed student entrepreneurship. This paper aims at improving our understanding on this by testing if digital and coding skills matter for entrepreneurial orientation and student entrepreneurship. Adopting a Human Capital and Social Capital Theory perspective, we hypnotized that these individual skills may have a statistically and positive impact on entrepreneurial orientation and student entrepreneurship. Based on Logit and Probit regression analyses on more than 2000 Italian university students, we confirmed our hypotheses.

Keywords: Student Entrepreneurship, Entrepreneurial University, Human Capital, Social Capital

1. Introduction

All around the world, universities are developing courses and strategies to foster entrepreneurial intention and student entrepreneurship (Wilson et al., 2007; Martin et al., 2013; Lyons and Zhang, 2018). While entrepreneurial intention refers only to students that declare an intention to start a business in the future (Liñán and Chen, 2009), student entrepreneurship addresses (or refers to) nascent entrepreneurs (i.e., students who are in the process of creating their own businesses) and active entrepreneurs (i.e., students who already own and are running their own businesses) (Bergmann et al., 2016; Sieger et al., 2016). With students' entrepreneurial orientation, instead, we are referring to both: entrepreneurial intention and student entrepreneurship. In other words, with students' entrepreneurial orientation we are referring to students that declare an intention to start a business or students that are nascent entrepreneurs or students that are active entrepreneurs.

This interest from universities for these topics derives from several aspects. First, universities represent a crucial environment to generate human capital and social capital that are essential to innovation and competitiveness (Guerrero et al., 2015). Second, university students (from any field of study and education level) are becoming more and more interested in entrepreneurship (Peterman and Kennedy, 2003; Lyons and Zhang, 2018), and some of them are willing to create their own businesses during their studies (Bergmann et al., 2016; Minola et al., 2016). For instance, university students are asking for entrepreneurship courses and support activities (Peterman and Kennedy, 2003; Lyons and Zhang, 2018). In fact, according to GUESSS reports, the number of students that have not attended a course on entrepreneurship decreased from 62.4% in 2014 (Sieger et al., 2014) to 55.4% in 2016 (Sieger et al., 2016). As a result, universities are creating several entrepreneurship courses and other activities to foster students' entrepreneurial orientation such as university incubators/accelerators (Kolympiris and Klein, 2017). Some examples are Helix[1] at Yale in the US, Student Startups Programmes[2] at University of Exeter in the UK and the Contamination Labs[3] in several Italian universities. In

[1] https://www.yalehelix.com/.

[2] https://business-school.exeter.ac.uk/research/centres/entrepreneurship/studentstartups/.

[3] https://clab.cineca.it/.

addition, students are developing student-led entrepreneurial organizations (Pittaway et al., 2011). Some global examples are the Junior Enterprises[4] and Enactus[5]. Moreover, several actors of the university entrepreneurial ecosystems (e.g., policymakers, organizations that support new venture creations and investors) are interested in it (e.g., O'Connor 2013; Hoppe, 2016, Wright et al., 2017). For instance, the OECD and the European Commission are currently developing and supporting several programs aimed at fostering students' entrepreneurial orientation (Fayolle, 2013). Indeed, in the Netherlands there is ASIF Ventures[6], a venture capital investing only in student start-ups. Finally, student start-ups also generate substantial economic impact (Roberts and Eesley, 2011; Astebro et al., 2012; Chiarello et al., 2021).

Although a great deal of attention has been paid to entrepreneurial intention (see Donaldson, 2019 for a recent literature review), only some studies (Bergmann et al., 2016; Minola et al., 2016; Laskovaia et al., 2017; Shirokova et al., 2018) have recently started to analyze which variables can foster student entrepreneurship. However, and most importantly, to our best knowledge, no one has yet tested individual-level factors such as coding and digital knowledge and experience on entrepreneurial orientation and student entrepreneurship. Nevertheless, analyzing Italian households and, therefore, not university students, Oggero et al., (2020) recently highlighted a positive correlation between digital skill and the probability of being an entrepreneur among men. In addition, due to the possibility and access of the digital world to entrepreneurship (Sussan and Acs, 2017), these aspects may be relevant. For instance, over the

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[4] https://www.juniorenterprises.org/.

[5] https://enactus.org/.

[6] https://www.asif.ventures/.

last two decades, digital entrepreneurs have increased (Srinivasan and Venkatraman 2018) since digital tools have reduced the barriers and made it easy to create a start-up (Sahut et al., 2021). Some of the most successful start-ups in the world such as Meta, Google and Microsoft were created by university students (Bergmann et al., 2016) with coding knowledge and experience. To fill these gaps, the aim of this study is to empirically test if coding and digital knowledge and experience may have a positive impact on entrepreneurial orientation and student entrepreneurship.

In order to test the hypotheses that coding and digital knowledge and experience have a positive impact on entrepreneurial orientation and student entrepreneurship, this study employs a unique data set of Italian university students. The sample is composed by 2608 Italian university students who answered a national survey in 2017. From a Human Capital Theory perspective, our results display that coding knowledge and experience have a positive impact on entrepreneurial orientation and student entrepreneurship. Moreover, from a Social Capital Theory perspective, our results show that digital knowledge and experience have a positive impact on entrepreneurial orientation and student entrepreneurship.

2. Hypotheses Development

2.1 Coding knowledge and experience

According to the Human Capital Theory, human capital consists of attributes that include education, experience, knowledge, and skills (Becker, 1994; Pfeffer, 1994; Florin et al., 2003). These attributes have long been argued to be a vital resource for entrepreneurial success (Davidsson and Honig, 2003; Colombo and Grilli, 2005; Unger et al., 2011). For instance, knowledge and experience are also considered to improve people's cognitive capacity, in addition to aiding in the integration and accumulation of new information, as well as the integration and adaptation to new circumstances (Davidsson and Honig, 2003). Therefore, individuals with more or higher quality human capital should be better at detecting and exploiting new opportunities (Davidsson and Honig, 2003; Colombo and Grilli, 2005; Unger et al., 2011). In our current information revolution, coding emerges as an important skill that is considered to improve the cognitive abilities of individuals (Oggero et al., 2020; Özcan et al., 2021), and it can be reasonably argued that knowledge and experience in coding increase the quality of human capital in our current world. Consequently, the higher quality human capital a person possesses, he should be better at spotting lucrative new economic activity opportunities if they exist thus more probability to choose the entrepreneurial path (Davidsson and Honig, 2003; Colombo and Grilli, 2005; Moog et al., 2015). The technological advancement has increased the role of individuals who can program, as coding has been part of the core of start-ups and enterprises during the last two decades, which sparked the billion dollars start-ups founded by students or recent graduates (Sahut et al., 2021) such as Google, Meta, and Dropbox. Furthermore, during the last two decades the barriers to creating a start-up have decreased significantly (Sahut et al., 2021), it became more apparent by the number of young entrepreneurs and students who created and developed tech companies that dominate the world now, and most of these founders are programmers, either studied programming or software engineering-related fields, or self-taught programmers such as the founders of Google, WhatsApp, and Alibaba (Bertoni, 2020). In this context, coding knowledge and experience have become a fundamental human capital attribute in the modern world for entrepreneurs. Moreover, although Davidsson and Honig, (2003) did not explicitly consider university students but based considered samples of established firms, they found out that human capital is important in predicting entrance into new ventures as human capital help in discovering entrepreneurial opportunities and subsequently in becoming an entrepreneur. Furthermore, Colombo and Piva, (2020) found out that students enrolled in university degree programs particularly in Science, Technology, Engineering, and Mathematics (STEM) fields after being subjected to scientific and technical knowledge, found to be more likely to identify and benefit from the knowledge by choosing entrepreneurship as a career. In conclusion, it is reasonable to assume our following hypotheses:

H1a. Coding knowledge has a positive impact on students' entrepreneurial orientation

H1b. Coding knowledge has a positive impact on students' entrepreneurship

H2a. Coding experience has a positive impact on students' entrepreneurial orientation

H2b. Coding experience has a positive impact on students' entrepreneurship

2.2 Digital knowledge and experience

The importance of knowledge and experience in using digital tools can be highlighted by the Social Capital Theory. As social capital can be broadly defined as the ability of an entrepreneur to extract and use resources from relationships to achieve desired objectives (Adler and Kwon, 2002). With the widespread of social networks and digital technologies that facilitate and ease access, strengthen and expand relationships and networks because of social capital bridging (Davidsson and Honig, 2003; Smith et al., 2017). Social capital is a fundamental part of entrepreneurial action and can be used to benefit from these digital resources in various ways that can vary from identifying potential opportunities to connecting with an angel investor or a venture capitalist (Davidsson and Honig, 2003; Nambisan, 2017). Our current digital economy owes a lot of its existence to the entrepreneurial activity that digital technology has enabled. Digital start-ups such as Google, Meta, Amazon, Alibaba, Dropbox, Uber, and Airbnb have risen to become global business giants. Indeed, the digital economy, with digital entrepreneurship at its core, has been hailed as one of the most significant economic developments since the industrial revolution (Zaheer et al., 2019). Beyond the social capital influence, digital tools allow the entrepreneurs to recognize and analyze market needs this change in innovation processes due to the spread of digital technologies across industries has made it easier to generate innovation in one part of the world it can market it in another part of the world (Nambisan, 2017). Also, the emergence of social media and streaming platforms has encouraged the appearance of a new type of young digital entrepreneurs. These new methods of creating, sharing, and exchanging information have created a vast amount of data and opportunities for entrepreneurs to build a business around it by either using them for marketing purposes or to reach customers or using the large amount of data to spot other opportunities. Furthermore, the easiness of earning money by using your phone and your digital knowledge has created a lot of opportunities for students and young entrepreneurs. In other words, this change in the complexity of skills, requirements, and tools to create value nowadays in comparison with the past, there has been a noticeable transformation with the digital revolution in businesses and occupations (Oggero et al., 2020). Which can be a catalyst for students and young adults to pursue an entrepreneurship career. For instance, Oggero et al., (2020) found a positive correlation between digital skills and the possibility of choosing entrepreneurship as a career. Moreover, Davidsson and Honig, (2003) discovered that social capital positively influences the individual to enter the entrepreneurial world when having entrepreneurs in their close network such as parents and/or close friends or neighbours. Thus, we would reasonably argue that the digital tools strengthen the social capital and consequently knowledge and experience of digital tools have a positive influence on entrepreneurial orientation and students' entrepreneurship as explain in our following hypotheses:

H3a. Digital knowledge has a positive impact on students' entrepreneurial orientation

H3b. Digital knowledge has a positive impact on students' entrepreneurship

H4a. Digital experience has a positive impact on students' entrepreneurial orientation

H4b. Digital experience has a positive impact on students' entrepreneurship

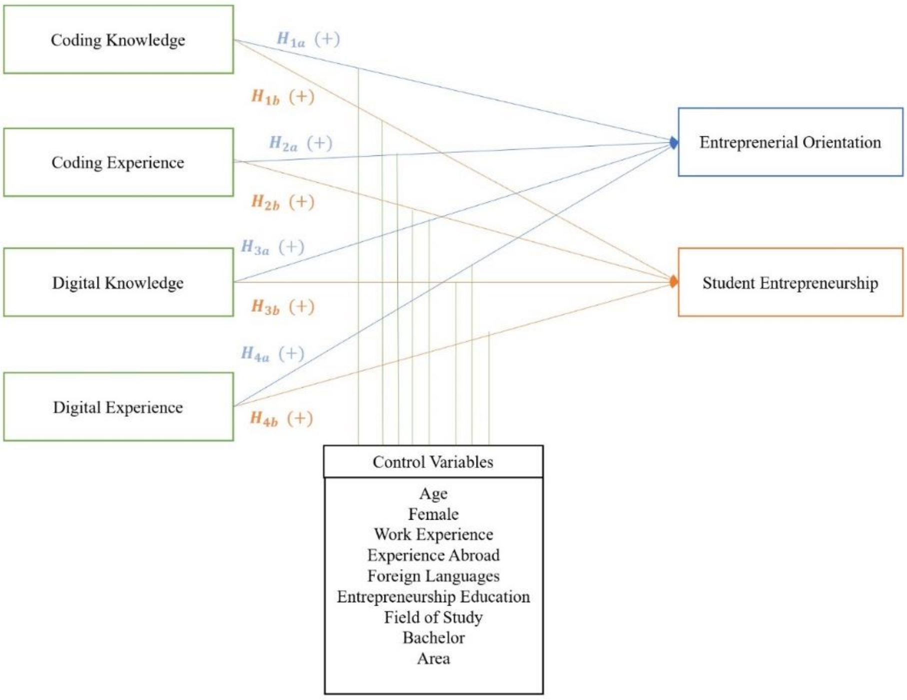

Figure 1 - Hypotheses

3. Research Design

3.1 Survey, data collection and sample

The questions and possible answers of our survey were taken from the literature of entrepreneurship (e.g., GUESSS survey) as well as by focus groups with experts of corporations. Several Human Resources as well as entrepreneurs and CEOs of international corporations were consulted to test and develop our survey. Moreover, a preliminary pilot research was carried out in 2015. In the pilot research of 2015, we were able to reach 2200 answers, 1389 of which were considered valid. This pilot was fundamental for our research in 2017 for several reasons. First, it allowed to test and revise our survey. Second, it allowed to test and revise how to contact university students. Third, it allowed to develop a database of about 15000 Italian university students from North to South Italy. However, we were aware that some of the students had already finished their university studies for the 2017 research, but they were included since there was a specific question regarding whether the respondent had graduated or not. Fourth, it also allowed to understand how to support the participants to properly answer our survey and to support them to avoid any misunderstanding. As a result, we assisted them in different ways to fill in the questionnaire, for instance, in person during some events. Fifth, the qualitative results of the pilot research were published in an Italian Report and presented and discussed at a national event in 2016 attended by representatives from several organizations such as the Italian Ministry of Education, University and Research (MIUR), University and Research, Digital360 Group, Gi Group, Engineering, IBM Italia, CheBanca!, Cisco, Hewlett Packard Enterprise, BravoSolution Italia, UniversityBox, Italtel, KPMG, Bip, and EconomyUp. However, the Italian Report did not present any regression analyses. All these activities carried out in the pilot research allow to develop our final survey for this study. For instance, the questions regarding the students' knowledge of foreign languages as well as their experience abroad were added in the survey for this study. One factor behind these additions is the fact that the international openness of university students may be relevant for entrepreneurship. Several studies (see Adesope et al., 2010 for a review) emphasized that persons who know two languages are gifted with stronger competences related to creativity and problem-solving. In addition, having had an experience abroad may have an impact on entrepreneurial intention (Fayolle and Gailly, 2015). In conclusion, the survey was composed of 42 questions divided into 4 main sections: general information, entrepreneurship, digital, and coding. Unfortunately, mostly due to privacy reasons, it is not possible to obtain the contact information of all the university students in a Country. Therefore, we were not able to define a random sample for our study. However, in order to perform our robust quantitative analyses, we did our best to reach a statistically representative sample of the population of Italian university students. To reach this goal, first we carried out the pilot research in 2015. Moreover, in 2017 we organized some physical events with some Italian universities in order to support the students in case of any questions. These physical events were organized in universities located in northern (e.g., Lombardy region), central (e.g., Tuscany region) and southern (e.g., Campania region) Italy. In addition to this, we involved some university Professors located in different Italian universities such as Bocconi University and University of Rome Tor Vergata. In the end, we received almost 4000 answers. Then, we performed a deep analysis of the answers received in order to clean our dataset. For instance, we deleted the answers that presented even only one ambiguous element. We also deleted the respondents who declared to be younger than 18 years old or older than 35 years old. Even if we know that some exceptions may exist in the ages of students, we preferred to consider these as outliers and, therefore, not suitable for our study. In addition, since we are focusing on universities students, we deleted the respondents who declared to have finished their studies. We also deleted the answers that were not fully complete to perform all our analyses with the same sample. In conclusion, we obtained a sample of 2608 answers. Finally, since our variables were obtained through a survey, as a preliminary test, as presented in similar studies (e.g., Minola et al., 2016), we checked for non-response bias (Oppenheim 1992) and multicollinearity (Hair et al., 2006). Given the results of our tests, none of these concerns affected our analyses. To make sure we have a reliable and statistically representative sample, we compared our sample with the official information available from the MIUR (http://dati.ustat.miur.it/) as well as with other datasets. According to the MIUR there were 1694824 university students in Italy in 2017. Based on our preliminary analyses, our sample is statistically representative of the population of Italian university students. Moreover, we compared our sample with some other datasets. The GUESSS Italian Report of 2018 based on 7122 answers highlighted that 30% had entrepreneurial intentions.[7] In line with this, our sample presents an average of 34% for entrepreneurial orientation (entrepreneurial intentions and student entrepreneurship). However, our sample presents lower percentages regarding nascent and active entrepreneurship (7% and 2% respectively) than the GUESSS Italian Report of 2018 (18% and 7% respectively). However, we believe that our sample better identified the Italian student activities regarding entrepreneurship since our study was not only focused on entrepreneurship as GUESSS. Therefore, we believe that there was a lower bias on the topic of entrepreneurship than in GUESSS. For instance, to participate in GUESSS, students receive an email with the term entrepreneurship stressed in the topic of the survey. As a result, students interested in entrepreneurship may be more motivated to answer

[7] The GUESSS Italian Report of 2018 is available here: https://www.guesssurvey.org/publications/publications/national-reports.html.

by creating a bias for GUESSS. Finally, as explained by literature (e.g., Acs and Karlsson 2002; Barbero et al., 2012) we decided to focus on Italy since it allowed to reduce the impact of different national policies and other contextual factors such as institutional environment. However, since the sample design was not random, the findings of this paper should be generalized with a note of caution.

3.2 Regression variables

Table 1 summarizes the variables for the regression analyses.

Outcome variables (dependent variables)	
NAME	**DESCRIPTION**
EO_i	dummy variable = 1 if the student *i* has the intention to start a business OR if the student *i* is currently trying to start a
$StudentEntre_i$	dummy variable = 1 if the student *i* is currently trying to start a business OR the student *i* is running a business; = 0
Predictor variables (independent variables)	
NAME	**DESCRIPTION**
$CodeKnowledge_i$	dummy variable = 1 if the student *i* knows how to code; =
$CodeExperience_i$	dummy variable = 1 if the student *i* developed a software
$DigSelfKnowledge_i$	dummy variable = 1 if the student *i* declares to have some knowledge on Mobile Advertising, Big Data, and
$DigTestKnowledge_i$	dummy variable = 1 if the student *i* correctly answered questions related to Mobile Advertising, Big Data, and

DigFullKnowledge$_i$	dummy variable = 1 if the student *i* declares to have some knowledge on Mobile Advertising, Big Data, Electronic Invoicing AND the student *i* correctly answered questions
DigExperience$_i$	dummy variable = 1 if the student *i* sold something online
Control variables (independent variables)	
NAME	**DESCRIPTION**
Age$_i$	age of the student *i*.
Female$_i$	dummy variable = 1 if the student *i* is a woman; 0 otherwise.
WorkExperience$_i$	dummy variable = 1 if the student *i* did a work experience;
ExperienceAbroad$_i$	dummy variable = 1 if the student *i* did an experience
ForeignLanguages$_i$	dummy variable = 1 if the student *i* knows more than 2
EntreEdu$_i$	dummy variable = 1 if the student *i* attended an
FieldStudy*i*	categorical variable = 0 if the student *i* is studying in the field of Science, Technology, Engineering and Mathematics (STEM); = 1 if the student *i* is studying in the
Bachelor$_i$	dummy variable = 1 if the student *i* is a bachelor student; 0 otherwise.
Area$_i$	categorical variable based on NUTS1 for Italy indicates the Area where the student *i* is studying.

Table 1: Regression variables

3.3 Regression models

In order to test our hypotheses, several Probit and Logit regression analyses were performed on the sample since our dependent variables are dummy variables (Maddala and Lahiri, 2006). For instance, several similar recent studies employed the same regression models such as Probit regression analyses by Colombo and Piva (2020) and Logit regression analyses by Minola et al., (2016).

The Logit and Probit regression models employed in this study share the following structure:

$$Entrepreneurship_i = f(Coding_i, Digital_i, X1_i,\ X2_i,\ \ldots,\ Xn_i,\ \gamma,\ \beta)$$

where:

- *Entrepreneurship*$_i$ represents the dependent variables assessing the students' entrepreneurial orientation or the student entrepreneur *i* (named EO and StudentEntre in Table 1);

- *Coding*$_i$ represents the predictor variables identifying coding knowledge or coding experience of the student *i* (named CodeKnowledge and CodeExperience in Table 1);

- *Digital*$_i$ represents the predictor variables identifying digital knowledge or digital experience of the student *i* (named DigSelfKnowledge, DigTestKnowledge, DigFullKnowledge, and DigExperience in Table 1);

- $X1_i$, $X2_i$, …, Xn_i are several control variables representing factors that could influence the interest in entrepreneurship of the student *i* (named Age, Female, WorkExperience, ExperienceAbroad, ForeignLanguages, EntreEdu, FieldStudy, Bachelor, and Area in Table 1);

- γ and β are vectors of the parameters to be estimated.

Therefore, the present study considered two dependent variables: the first one on entrepreneurial orientation, the second one on student entrepreneurship. Moreover, we applied three different variables to measure digital knowledge (named DigSelfKnowledge, DigTestKnowledge, and DigFullKnowledge in Table 1). However, to avoid any multicollinearity issues, we did not include more than one variable on digital knowledge in the same regression model. In addition, the correlation among variables has been checked (Appendix A). For instance, we did not include the variables regarding coding knowledge and coding experience in the same regression model to avoid multicollinearity issues since their correlation is higher than 0.5. This logically derives from the fact that in order to develop a software or an application (variable CodeExperience), the student has to know how to code (variable CodeKnowledge). We would also like to highlight the fact that several regression models were executed with other dependent and independent variables. For instance, we performed all our regression models with another dependent variable focused only on students who are running businesses (also known as active entrepreneurs). We also ran all our regression models with other dependent variables regarding digital knowledge and digital experience. All these additional tests led to the same results present in the Results section. However, we can share these analyses upon request. All the regression analyses were performed with Stata Software with robust standard errors.

4. Results

Table 2 presents some qualitative information about our sample.

	Observation	Mean	Median	SD	MIN	MAX
EO	2608	0.34	0	0.47	0	1
StudentEntre	2608	0.09	0	0.29	0	1
CodeKnowledge	2608	0.49	0	0.50	0	1
CodeExperience	2608	0.29	0	0.45	0	1
DigSelfKnowledge	2608	0.27	0	0.44	0	1
DigTestKnowledge	2608	0.11	0	0.31	0	1
DigFullKnowledge	2608	0.05	0	0.23	0	1
DigExperience	2608	0.43	0	0.45	0	1
Age	2608	22.38	22	2.59	18	35
Female	2608	0.62	1	0.49	0	1
WorkExperience	2608	0.55	1	0.50	0	1
ExperienceAbroad	2608	0.28	0	0.45	0	1
ForeignLanguages	2608	0.12	0	0.33	0	1
EntreEdu	2608	0.21	0	0.4	0	1
FieldStudy	2608	0.52	0	0.56	0	2
Bachelor	2608	0.74	1	0.44	0	1
Area	2608	2.89	3	1.19	1	5

Table 2 - Summary statistics of the regression variables

Regarding the dependent variables, as it is possible to see from Table 2, on average, 34% of the respondents have entrepreneurial orientation. However, on average, only 9% of them are student entrepreneurs (also defined as nascent and active entrepreneurs). Regarding the predictor variables, as was easily guessed, the average percentage of students with coding experience is lower than the average percentage of students with coding knowledge. In fact, even if a student knows how to code, it does not necessarily indicate that the student has tested their knowledge in practice. On the contrary, and interestingly, the average percentage of students with digital experience is higher than the average percentage of students with digital knowledge. This is probably due to the fact that students, and generally any person, may have experience in the digital world without having any specific, or almost any, digital knowledge. Finally, regarding the control variables, we can notice that, on average, the majority of the respondents are female students, 55% of them had a work experience, 28% of them had an experience abroad, 12% know more than 2 languages in addition to Italian, 21% attended an entrepreneurship course and the large majority (74%) are bachelor students. Then, to test our hypotheses we run several Probit and Logit regression analyses. To show these analyses, we divided our Results section into two sub-sections. The first one aims at testing the hypotheses H1a, H2a, H3a, and H4a regarding entrepreneurial orientation. The second one aims at testing the hypotheses H1b, H2b, H3b, and H4b regarding student entrepreneurship. We tested all the hypotheses with Probit and Logit regression analyses.

4.1 Hypotheses test on Entrepreneurial Orientation

	CodeKnowledge		CodeExperience		DigKnowledge1		DigKnowledge2		DigKnowledge3		DigExperiences	
CodeKnowledge	0.46***	(0.09)										
CodeExperience			0.43***	(0.10)								
DigSelfKnowledge					0.69***	(0.10)						
DigTestKnowledge							0.65***	(0.14)				
DigFullKnowledge									0.67***	(0.19)		
DigExperience											0.72***	(0.09)
Age	0.04**	(0.02)	0.04**	(0.02)	0.04**	(0.02)	0.04**	(0.02)	0.04**	(0.02)	0.04*	(0.02)
Female	-0.51***	(0.09)	-0.49***	(0.09)	-0.46***	(0.10)	-0.56***	(0.09)	-0.54***	(0.09)	-0.41***	(0.10)
WorkExperience	0.80***	(0.09)	0.79***	(0.09)	0.73***	(0.09)	0.80***	(0.09)	0.79***	(0.09)	0.73***	(0.09)
ExperienceAbroad	-0.23**	(0.10)	-0.25**	(0.10)	-0.21**	(0.10)	-0.20*	(0.10)	-0.20**	(0.10)	-0.21**	(0.10)
ForeignLanguages	0.19	(0.14)	0.19	(0.14)	0.18	(0.14)	0.24*	(0.14)	0.23	(0.14)	0.16	(0.14)
EntreEdu	0.81***	(0.11)	0.80***	(0.11)	0.73***	(0.11)	0.81***	(0.11)	0.81***	(0.11)	0.84***	(0.11)
Bachelor	0.27**	(0.11)	0.28**	(0.11)	0.31**	(0.11)	0.30**	(0.11)	0.29**	(0.11)	0.26**	(0.11)
Constant	-2.62***	(0.48)	-2.55***	(0.48)	-2.55***	(0.48)	-2.53***	(0.47)	-2.44***	(0.47)	-2.62***	(0.48)
Observations	2608		2608		2608		2608		2608		2608	
Log likelihood	-1.530e+03		-1.533e+03		-1.518e+03		-1.531e+03		-1.536e+03		-1.511e+03	
Prob > chi2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.0854		0.0833		0.0924		0.0847		0.0815		0.0967	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 3 - Logit regression models Dependent variable: Entrepreneurial Orientation

	CodeKnowledge		CodeExperience		DigKnowledge1		DigKnowledge2		DigKnowledge3		DigExperiences	
CodeKnowledge	0.28^{***}	(0.05)										
CodeExperience			0.26^{***}	(0.06)								
DigSelfKnowledge					0.42^{***}	(0.06)						
DigTestKnowledge							0.40^{***}	(0.08)				
DigFullKnowledge									0.41^{***}	(0.12)		
DigExperience											0.44^{***}	(0.05)
Age	0.02^{**}	(0.01)	0.02^{**}	(0.01)	0.02^{*}	(0.01)	0.02^{**}	(0.01)	0.02^{**}	(0.01)	0.02^{*}	(0.01)
Female	-0.30^{***}	(0.06)	-0.29^{***}	(0.06)	-0.28^{***}	(0.06)	-0.33^{***}	(0.06)	-0.32^{***}	(0.06)	-0.24^{***}	(0.06)
WorkExperience	0.48^{***}	(0.06)	0.48^{***}	(0.06)	0.43^{***}	(0.06)	0.48^{***}	(0.06)	0.47^{***}	(0.06)	0.44^{***}	(0.06)
ExperienceAbroad	-0.14^{**}	(0.06)	-0.15^{**}	(0.06)	-0.12^{**}	(0.06)	-0.12^{*}	(0.06)	-0.12^{**}	(0.06)	-0.13^{**}	(0.06)
ForeignLanguages	0.12	(0.08)	0.12	(0.08)	0.11	(0.08)	0.15^{*}	(0.08)	0.14^{*}	(0.08)	0.10	(0.08)
EntreEdu	0.50^{***}	(0.06)	0.49^{***}	(0.06)	0.45^{***}	(0.07)	0.50^{***}	(0.06)	0.50^{***}	(0.06)	0.51^{***}	(0.06)
Bachelor	0.16^{**}	(0.07)	0.16^{**}	(0.07)	0.18^{**}	(0.07)	0.17^{**}	(0.07)	0.17^{**}	(0.07)	0.15^{**}	(0.07)
Constant	-1.57^{***}	(0.29)	-1.53^{***}	(0.29)	-1.53^{***}	(0.29)	-1.52^{***}	(0.29)	-1.46^{***}	(0.29)	-1.56^{***}	(0.29)
Observations	2608		2608		2608		2608		2608		2608	
Log likelihood	-1.530e+03		-1.534e+03		-1.519e+03		-1.531e+03		-1.537e+03		-1.511e+03	
Prob > chi2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.0852		0.0832		0.0921		0.0845		0.0813		0.0965	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 4 - Probit regression models Dependent variable: Entrepreneurial Orientation

	Logit regression				Probit regression			
	CodeKnowledge DigKnowledge&Experiences		CodeExperience DigKnowledge&Experience		CodeKnowledge DigKnowledge&Experiences		Code Experience DigKnowledge&Experience	
CodeKnowledge	0.37***	(0.09)			0.22***	(0.06)		
CodeExperience			0.29**	(0.10)			0.18**	(0.06)
DigFullKnowledge	0.57**	(0.19)	0.56**	(0.19)	0.34**	(0.12)	0.34**	(0.12)
DigExperience	0.68***	(0.09)	0.68***	(0.09)	0.41***	(0.06)	0.41***	(0.06)
Age	0.04*	(0.02)	0.04*	(0.02)	0.02*	(0.01)	0.02*	(0.01)
Female	-0.36***	(0.10)	-0.36***	(0.10)	-0.21***	(0.06)	-0.21***	(0.06)
WorkExperience	0.70***	(0.09)	0.70***	(0.09)	0.42***	(0.06)	0.42***	(0.06)
ExperienceAbroad	-0.22**	(0.10)	-0.22**	(0.10)	-0.13**	(0.06)	-0.14**	(0.06)
ForeignLanguages	0.12	(0.14)	0.13	(0.14)	0.08	(0.09)	0.09	(0.09)
EntreEdu	0.79***	(0.11)	0.78***	(0.11)	0.48***	(0.07)	0.48***	(0.07)
Bachelor	0.25**	(0.12)	0.27**	(0.11)	0.15**	(0.07)	0.15**	(0.07)
Constant	-2.83***	(0.48)	-2.75***	(0.48)	-1.70***	(0.29)	-1.64***	(0.29)
Observations	2608		2608		2608		2608	
Log likelihood	-1.497e+03		-1.502e+03		-1.498e+03		-1.502e+03	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.1049		0.1023		0.1046		0.1021	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 5 – Logit and Probit regression models Dependent variable: Entrepreneurial Orientation

4.2 Hypotheses test on Student Entrepreneurship

	CodeKnowledge		CodeExperience		DigKnowledge1		DigKnowledge2		DigKnowledge3		DigExperiences	
CodeKnowledge	0.65^{***}	(0.16)										
CodeExperience			0.84^{***}	(0.16)								
DigSelfKnowledge					0.98^{***}	(0.15)						
DigTestKnowledge							0.58^{**}	(0.19)				
DigFullKnowledge									0.75^{**}	(0.23)		
DigExperience											0.79^{***}	(0.16)
Age	0.08^{**}	(0.03)	0.08^{**}	(0.03)	0.08^{**}	(0.03)	0.08^{**}	(0.03)	0.08^{**}	(0.03)	0.08^{**}	(0.03)
Female	-0.85^{***}	(0.16)	-0.80^{***}	(0.16)	-0.78^{***}	(0.16)	-0.91^{***}	(0.15)	-0.88^{***}	(0.15)	-0.74^{***}	(0.16)
WorkExperience	1.18^{***}	(0.18)	1.14^{***}	(0.18)	1.04^{***}	(0.18)	1.18^{***}	(0.18)	1.16^{***}	(0.18)	1.09^{***}	(0.18)
ExperienceAbroad	0.19	(0.16)	0.15	(0.17)	0.22	(0.17)	0.24	(0.16)	0.24	(0.16)	0.23	(0.16)
ForeignLanguages	0.19	(0.23)	0.15	(0.23)	0.15	(0.24)	0.23	(0.23)	0.22	(0.23)	0.18	(0.23)
EntreEdu	1.07^{***}	(0.16)	1.04^{***}	(0.16)	0.93^{***}	(0.16)	1.09^{***}	(0.16)	1.07^{***}	(0.16)	1.12^{***}	(0.16)
Bachelor	0.30	(0.18)	0.32^{*}	(0.19)	0.37^{*}	(0.19)	0.34^{*}	(0.18)	0.34^{*}	(0.18)	0.31^{*}	(0.19)
Constant	-5.84^{***}	(0.76)	-5.81^{***}	(0.76)	-5.76^{***}	(0.78)	-5.65^{***}	(0.74)	-5.60^{***}	(0.74)	-5.89^{***}	(0.77)
Observations	2608		2608		2608		2608		2608		2608	
Log likelihood	-670.27243		-664.21112		-658.64151		-674.86897		-674.14677		-665.68407	
Prob > chi2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.1462		0.1539		0.1610		0.1403		0.1412		0.1520	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 6 – Logit regression models Dependent variable: Student Entrepreneurship

	CodeKnowledge		CodeExperience		DigKnowledge1		DigKnowledge2		DigKnowledge3		DigExperiences	
CodeKnowledge	0.35***	(0.08)										
CodeExperience			0.46***	(0.08)								
DigSelfKnowledge					0.52***	(0.08)						
DigTestKnowledge							0.30**	(0.10)				
DigFullKnowledge									0.41**	(0.13)		
DigExperience											0.40***	(0.08)
Age	0.04**	(0.02)	0.04**	(0.02)	0.04**	(0.02)	0.04**	(0.01)	0.04**	(0.01)	0.04**	(0.02)
Female	-0.44***	(0.08)	-0.41***	(0.08)	-0.40***	(0.08)	-0.47***	(0.08)	-0.45***	(0.08)	-0.39***	(0.08)
WorkExperience	0.59***	(0.09)	0.58***	(0.09)	0.52***	(0.09)	0.59***	(0.09)	0.58***	(0.09)	0.55***	(0.09)
ExperienceAbroad	0.11	(0.08)	0.09	(0.09)	0.13	(0.09)	0.14	(0.08)	0.14	(0.08)	0.13	(0.09)
ForeignLanguages	0.13	(0.12)	0.11	(0.12)	0.10	(0.12)	0.16	(0.12)	0.15	(0.12)	0.13	(0.12)
EntreEdu	0.58***	(0.08)	0.56***	(0.08)	0.52***	(0.08)	0.59***	(0.08)	0.58***	(0.08)	0.60***	(0.08)
Bachelor	0.16*	(0.09)	0.18*	(0.09)	0.20**	(0.10)	0.19**	(0.09)	0.19**	(0.09)	0.16*	(0.10)
Constant	-3.15***	(0.39)	-3.17***	(0.39)	-3.13***	(0.40)	-3.03***	(0.39)	-3.00***	(0.39)	-3.14***	(0.40)
Observations	2608		2608		2608		2608		2608		2608	
Log likelihood	-668.31799		-662.16696		-657.14955		-674.18816		-673.27977		-665.02305	
Prob > chi2	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.1487		0.1565		0.1629		0.1412		0.1424		0.1529	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 7 – Probit regression models Dependent variable: Student Entrepreneurship

	Logit regression				Probit regression			
	CodeKnowledge DigKnowledge&Experiences		CodeExperience DigKnowledge&Experience		CodeKnowledge DigKnowledge&Experiences		Code Experience DigKnowledge&Experience	
CodeKnowledge	0.54^{**}	(0.17)			0.29^{***}	(0.08)		
CodeExperience			0.70^{***}	(0.16)			0.38^{***}	(0.08)
DigFullKnowledge	0.61^{**}	(0.23)	0.55^{**}	(0.23)	0.34^{**}	(0.13)	0.30^{**}	(0.13)
DigExperience	0.71^{***}	(0.16)	0.67^{***}	(0.16)	0.36^{***}	(0.08)	0.34^{***}	(0.08)
Age	0.08^{**}	(0.03)	0.08^{**}	(0.03)	0.04^{**}	(0.01)	0.04^{**}	(0.02)
Female	-0.70^{***}	(0.16)	-0.66^{***}	(0.16)	-0.37^{***}	(0.08)	-0.35^{***}	(0.08)
WorkExperience	1.05^{***}	(0.18)	1.03^{***}	(0.18)	0.54^{***}	(0.09)	0.52^{***}	(0.09)
ExperienceAbroad	0.22	(0.17)	0.18	(0.17)	0.12	(0.09)	0.11	(0.09)
ForeignLanguages	0.11	(0.24)	0.10	(0.24)	0.10	(0.12)	0.09	(0.12)
EntreEdu	1.04^{***}	(0.16)	1.02^{***}	(0.16)	0.56^{***}	(0.08)	0.55^{***}	(0.08)
Bachelor	0.30	(0.19)	0.31^{*}	(0.19)	0.16^{*}	(0.10)	0.17^{*}	(0.10)
Constant	-6.17^{***}	(0.77)	-6.13^{***}	(0.76)	-3.29^{***}	(0.40)	-3.30^{***}	(0.40)
Observations	2608		2608		2608		2608	
Log likelihood	-656.13769		-652.19214		-654.54932		-650.61737	
Prob > chi2	0.0000		0.0000		0.0000		0.0000	
Pseudo R2	0.1642		0.1692		0.1662		0.1712	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

Dummy variables regarding the categorical variables Field Study and Area were included in all the Models.

Table 8 – Logit and Probit regression models Dependent variable: Student Entrepreneurship

Furthermore, we performed several robustness checks on our regression models. For all the predictor variables we performed eight additional regression models by adding one control variable for each model. To give an example, we ran the model "CodeKnowledge" of Table 3 only with the control variable Age; then with the control variables Age and Female; then with the control variables Age, Female, and WorkExperience; then with the control variables Age, Female, WorkExperience, and ExperienceAbroad; then with the control variables Age, Female, WorkExperience, ExperienceAbroad, and ForeignLanguages; then with the control variables Age, Female, WorkExperience, ExperienceAbroad, ForeignLanguages, and EntreEdu; then with the control variables Age, Female, WorkExperience, ExperienceAbroad, ForeignLanguages, EntreEdu, and i.FieldStudy; then with the control variables Age, Female, WorkExperience, ExperienceAbroad, ForeignLanguages, EntreEdu, i.FieldStudy, and Bachelor; then with all the control variables as shown in the model "CodeKnowledge" of Table 3. All our robustness checks as well as all the analyses presented in Tables 3, 4, 5, 6, 7, and 8 showed that all our hypotheses H1a, H1b, H2a, H2b, H3a, H3b, H4a, and H4b are confirmed. We tested H1a, H2a, H3a, and H4a with Tables 3, 4 and 5 where all our predictor variables regarding coding and digital knowledge and experience have a statistically significant and positive impact on entrepreneurial orientation. We tested H1b, H2b, H3b, and H4b with Tables 6, 7 and 8 where all our predictor variables regarding coding and digital knowledge and experience have a statistically significant and positive impact on student entrepreneurship.

5. Conclusion

In this study, on the basis of the Human Capital and the Social Capital Theories we hypothesized that digital and coding skills matter for students' entrepreneurial orientation and student entrepreneurship. To test these hypotheses, we employed a unique dataset of 2608 Italian university students who answered a national survey in 2017. All these hypotheses were verified with Probit and Logit regression analyses. Moreover, we performed several additional robustness analyses. In conclusion, we discovered that both factors have a statistically significant and positive impact on entrepreneurial orientation and student entrepreneurship.

Our study is not without limitations. The main limitation is the possibility of reverse causality between our dependent and independent variables. For instance, students may decide to improve their coding and digital knowledge and experience because they already have entrepreneurial intentions, or they are already nascent or active entrepreneurs. However, we can hypothesize that this mutual reverse causality is limited due to the young age of our sample. Many young people present an interest in coding and digital knowledge and experience before being interested in entrepreneurship. In any case, we suggest future studies to test our results with an instrumental variable and/or panel dataset to reduce this problem. Furthermore, future studies may employ pre- and post-surveys to reduce this issue. Another limitation is that we could not consider some other variables that may be relevant, such as if one or both the parents of the student are or were an entrepreneur, or the level of the family income status of the student, or the entrepreneurial university culture of the student. Future studies may consider these variables. The self-declarations of students can also be a limitation. In order to reduce this problem, we assisted the students in different ways to fill in the questionnaire to avoid any misunderstanding. For instance, this work is based on the second edition of a national study. Therefore, we tested the survey in a previous edition. Moreover, during our collection analysis, we had also assisted the students to fill in the questionnaire in person during some events. In addition to this, even if some preliminary tests show that our sample can be considered statistically representative of the population of Italian university students, since the sample design was not random, the findings of this paper should be generalized with a note of caution. Future studies may test our findings in other Countries. Moreover, our variables regarding coding and digital knowledge and experience are new and not validated in the literature. Future studies may use more internationally and theoretically validated questions in order to measure these individual aspects. Finally, we did not consider the recent development of no-code or low-code platforms as well as the support of Artificial Intelligence (AI) for coding. This may have an impact for the coding experiences of students.

Even if this study presents some limitations, we believe our results offer several theoretical and practical contributions. To our best knowledge, our study is the first one that test individual-level factors regarding coding and digital knowledge and experience in the entrepreneurship literature. We empirically tested the impact of individual factors regarding coding and digital knowledge and experience on entrepreneurship. Moreover, we did not focus only on entrepreneurial intentions due to a discussion on entrepreneurship studies regarding whether the establishment of entrepreneurial intention is worth analyzing, since that intention may not materialize (Hsu et al., 2019). Therefore, we improved our theoretical understanding on which factors may foster not only entrepreneurial intention but also student entrepreneurship. Since we discovered a statistically positive impact of coding and digital knowledge and experience on entrepreneurial orientation and student entrepreneurship, we suggested to include these variables in future surveys and projects (e.g., the new edition of GUESSS). In addition, corporations and organizations interested in students with entrepreneurial intention or in student entrepreneurship may be interested in our findings. As a matter of fact, as for the pilot study of 2015, also the qualitative results of this research were presented in an Italian Report and presented and discussed at a national event in 2017 attended by representatives from several large organizations such as the MIUR, Digital360 Group, Enel Foundation Generali Italia, Banca Popolare Sondrio, Cisco, QiBit, and SAS. In this event, three representatives of active student entrepreneurs were also present. However, the results presented and discussed were only qualitative. Finally, our study suggests supporting coding and digital knowledge and experience in all university activities that aim at fostering entrepreneurial orientation and student entrepreneurship. Future entrepreneurship courses, for instance, may consider incorporating coding and digital aspects.

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Appendix A – Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 EO	1																
2 StudentEntre	0.44*	1															
3 CodeKnowledge	0.13*	0.12*	1														
4 CodeExperience	0.13*	0.17*	0.65*	1													
5 DigSelfKnowledge	0.22*	0.22*	0.25*	0.31*	1												
6 DigTestKnowledge	0.12*	0.08*	0.08*	0.09*	0.17*	1											
7 DigFullKnowledge	0.12*	0.12*	0.10*	0.15*	0.39*	0.68*	1										
8 DigExperience	0.22*	0.16*	0.16*	0.21*	0.17*	0.08*	0.08*	1									
9 Age	0.06*	0.08*	0.01	0.02	0.07*	0.00	0.03	0.04*	1								
10 Female	-0.12*	-0.14*	-0.16*	-0.21*	-0.18*	-0.03	-0.08*	-0.21*	-0.06*	1							
11 WorkExperience	0.21*	0.17*	0.06*	0.09*	0.17*	0.07*	0.12*	0.16*	0.12*	-0.02	1						
12 ExperienceAbroad	-0.02	0.05*	0.06*	0.11*	0.02	-0.03	-0.01	0.01	0.03	-0.01	0.04	1					
13 ForeignLanguages	0.04	0.03	0.05*	0.05*	0.05*	-0.00	0.01	0.05*	-0.04*	0.11*	0.05*	0.216*	1				
14 EntreEdu	0.20*	0.20*	0.09*	0.13*	0.21*	0.08*	0.12*	0.08*	0.06*	-0.11*	0.13*	0.076*	0.053*	1			
15 FieldStudy	0.08*	0.04	-0.12*	-0.12*	0.00	-0.02	-0.01	-0.01	0.04*	0.21*	0.13*	-0.037	0.109*	0.05*	1		
16 Bachelor	0.04	0.01	0.03	0.00	-0.05*	-0.01	-0.02	0.03	-0.43*	-0.02	-0.05*	-0.079*	0.017	-0.02	0.02	1	
17 Area	-0.02	-0.02	-0.03	-0.03	-0.04	-0.02	-0.02	0.03	0.02	0.04	-0.01	0.009	-0.010	-0.07*	-0.09*	-0.03	1