Associate Professor Alexandra FRĂȚILĂ (ADAM), PhD
E-mail: alexandra.adam@economie.ase.ro
Department of Economics and Economic Policies
The Bucharest University of Economic Studies
Associate Professor Ioana Andrada GAVRIL (MOLDOVAN), PhD
E-mail: ioana.moldovan@economie.ase.ro
Department of Economics and Economic Policies
The Bucharest University of Economic Studies
Associate Professor Irina Elena PETRESCU, PhD
E-mail: irina.petrescu@eam.ase.ro
Department of Agrifood and Environmental Economics
The Bucharest University of Economic Studies
Professor Constanța POPESCU, PhD
E-mail: constanta.popescu@valahia.ro
Department of IOSUD Management
Valahia University of Târgoviște

STRUCTURAL SOCIO-ECONOMIC FACTORS ENHANCING M-COMMERCE: A MACROECONOMIC PERSPECTIVE OVER THREE CLUSTERS OF THE EU27

Abstract. *Alongside economic development, trade enhancement and digitalization, both e-commerce and m-commerce have increased gradually over the last decade and are forecasted to increase further over the following years. In the latest years, one of the most important catalyzers of these evolutions was the emergence of the COVID–19 pandemic. Within this paper, we aim at assessing the impact of some structural economic and social factors upon m-commerce. Specifically, we test the relationship between m-commerce and digitalization, education, economic growth, unemployment and income inequalities within three different clusters of countries of the European Union, for the period 2010 – 2020, using panel date regression models. Our results confirm a positive relationship between m-commerce and digitalization, education and economic growth, while showing a negative link between m-commerce and unemployment in all clusters. On the other hand, our empirical analysis concludes upon quite different results across the three clusters, when considering the relationship between m-commerce and income inequalities.*

Keywords*: m-commerce, digitalization, education, economic growth, unemployment, income inequalities, panel data analysis*

JEL Classification : L81, E21, F14, D63, I30

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1. Introduction

M-commerce is a rather new concept, focusing on the commercial activities performed through an internet connection and from a mobile, wireless device. M-commerce includes several activities: sales and purchases of goods and services, online banking, bill payment and all kinds of other online transactions, and is part of the e-commerce, which refers to all kinds of commercial transactions performed through the internet, both from wired and wireless devices (Tech Target, 2021).

Alongside economic development, trade enhancement and digitalization, both e-commerce and m-commerce have increased gradually over the last decade and are forecasted to increase further over the following years. The global m-commerce market was estimated at US$ 1.9 Trillion in 2020 and is projected to grow at a compounded annual rate of almost 20% by 2027, when it is estimated to reach US$ 6.6 Trillion (Global Industry Analysts, 2021). The growth rate is expected to have different intensities across the World, projected to be larger in China (almost 25% over the period 2020 - 2027). At the same time, in the EU, Germany would register a compounded annual growth rate of 17%, while Japan and Canada are expected to see raises of about 16% and 18% respectively, over the until 2027.

Apart from the rise of online purchases, there is a clear trend established in the last years that regards the increase of the share of m-commerce activities in the total e-commerce activities (Vărzaru and Bocean, 2021). This share was estimated to about 52% in 2016 and is forecasted to rise to almost 73% by the end of 2021, and, considering the rapid growth of online purchases, one can conclude that the majority of the additional online purchases are realized through a mobile device (Loesche, 2018).

One of the most important catalyzers of these evolutions was the emergence of the COVID–19 pandemic. In the circumstances of the wide range of restrictions aiming at social distancing, people resorted to online shopping, in order to meet their needs (Vărzaru and Bocean, 2021). According to some studies, online purchases increased by 40% in 2020, while the frequency of attending the shopping centers decreased by up to 45% (Dumanska et al., 2021). The frequency of online shopping differs across regions and countries, but Worldwide, all the regions have experienced a raise in online transactions conducted via a mobile device, with Asia-Pacific accounting for about half of the global m-commerce (Business Wire, 2021).

In the EU, the largest shares of individuals using mobile devices for commercial activities are reported for developed and sophisticated economies such as Denmark, Germany, Netherlands and Sweden.

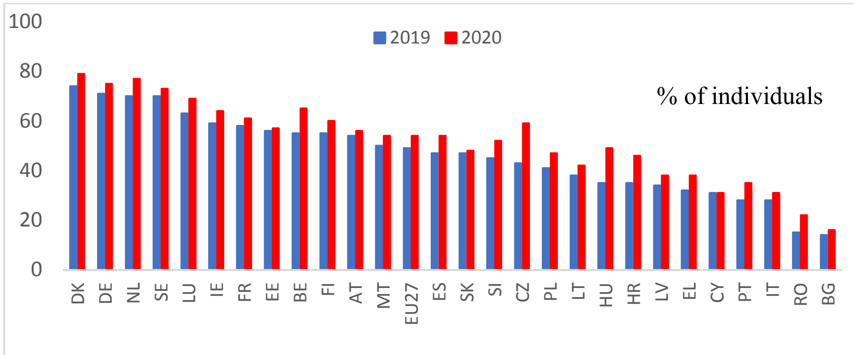

Figure 1. Internet purchases by individuals: Last online purchase in the last three months

In such countries, more than 70% of the individuals use e-commerce facilities (Figure 1). At the same time, in 2019, the lowest shares of individuals using online purchases were reported for Italy, Bulgaria and Romania. However, all the EU27 countries have seen intensifications of the online purchases in 2020, in the context of the pandemic, with the highest raises being reported for some CEE countries (Czech Republic, Hungary and Croatia). All in all, generally, the developing countries registered higher increases than the developed ones in 2020 (Figure 1).

Apart from increasing the e-commerce and m-commerce activities, The Covid-19 pandemic has led to changes in consumer behavior, diminishing borders in the sales of goods and even the enhancement of technology, alongside the growing influence of the Internet upon economy and global connections (Dumanska et al., 2021).

In this paper, we test the relationship between m-commerce and unemployment, inequalities, education, digitalization and economic growth within three different clusters of countries of the European Union, for the period 2010 – 2020. The remainder of this paper is structured as follows: Section 2 deals with the literature review, Section 3 presents the data and methodology, Section 4 includes the results of the empirical analysis and the last section concludes and formulates some discussion points for further research. To the best of our knowledge, this is among of the few papers in the literature aiming at determining the impact of social and economic structural factors upon m-commerce activities, in a macroeconomic framework.

2. Literature Review

As mentioned before, e-commerce and m-commerce are rather new concepts and topics in the literature (Luo and Niu, 2019). The majority of the studies found in the related literature regard mainly e-commerce activities and are most often conducted on a microeconomic basis. Only a relatively small number of papers tackle e-commerce in a macroeconomic framework. However, since m-commerce is part of e-commerce activities, we can state that the difference between e-commerce and m-commerce is rather reduced and not very significant when regarding structural factors of influence, or the channels of influence upon relevant macroeconomic variables. Therefore, we consider that the macroeconomic factors impacting e-commerce are also factors of influence for m-commerce.

In the pandemic context, there has been an intensification of the researchers` interests in this field, on the background of the recent developments determined by the Covid-19 crisis (Gu et al., 2021), focusing most on microeconomic aspects, phenomena and behaviors.

A study prepared by the Joint Research Center (Cardona et al., 2015) shows that cross border online commerce has a positive effect on the European Union GDP through different channels, while reducing trade costs and enhancing retail efficiency gains, which in turn lead to an increase in production in other sectors and in household consumption. Moreover, empirical evidence shows that, for BRICS countries and Turkey, e-commerce is an important determinant of economic growth, through innovation technology and higher investments (Yurtkur and Bahtyiar, 2020).

As regards unemployment, the channels of influence are diversified and also include some kinds of interdependencies. The literature in this field mostly tackles the positive effect of e-commerce on job creation, which can be considered equivalent to a negative influence of e-commerce or m-commerce upon the dynamics of unemployment. Some authors state that the labor market effect of e-commerce might be misunderstood and that "e-commerce is primarily a machine for turning unpaid household hours shopping into paid market work". Therefore, e-commerce is a net job creator, rather than a job destroyer (Mandel, 2017).

Several studies regarding the e-commerce development in rural China show that people involved in e-commerce activities have higher income, gain wealth and live better lives. However, there are some distributional effects worth mentioned: wealthy people tend to gain mode from e-commerce compared to the less wealthy in absolute terms, but the increase of the income of the latter in relative terms is higher (Luo and Niu, 2019).

On the other hand, some papers state that e-commerce has a negative effect on income inequalities. This is explained as follows: shifting jobs from traditional commercial activities to e-commerce, where wages are higher, will help diminishing the pay gap compared to workers in other sectors. E-commerce workers are mainly located in warehouses and logistic retail centers and are paid better than workers in traditional shopping centers, given the fact that they work hard, using a mix of cognitive and physical skills similar to industrial workers. In some cases, such workers earn by 30% more than traditional commercial workers, which leads to a reduction of the income gap compared to other sectors of the economy (Mandel, 2017). In this way, e-commerce contributes to declining income inequalities.

Education is considered among the main factors that influence economic development, as it positively influences social wellness and economic growth, diminishes social inequalities and promotes social mobility, innovation and technology (Opazo et al., 2021). Given all these, education is likely to influence the preferences for the way people achieve goods and services in order to meet their needs, so that we considered it suitable to assess the influence of education on m-commerce. When assessing the impact of e-commerce upon rural population in China, Luo and Niu (2021) state that it seems hard for people living in villages, with limited education, to fully take advantage of its benefits, while the most highly educated (e.g. those who attended technical school) were the ones with the highest gains.

As regards digitalization, it is considered a decisive factor of m-commerce, as this in turn is enhanced by the internet connections and the development of new devices and apps. Digital technology is recognized as an important factor to speed up the activities in the economy, while the Internet and digital devices are considered an important driver of economic growth, as the digital technologies facilitate the trade of goods and services through e-commerce (Afonasova et al., 2019).

For governments around the world, the implementation of digital technologies represents a policy goal (Gruber, 2017), which becomes more and more important, especially in Europe, in the context of the Next Generation EU plan, that has as main goals digitalization and green transition, as reforms meant to enhance the recovery and resilience of the EU economies, in the context of the Covid-19 pandemic. The expansion of the digital sector has been a key driver of economic growth in recent years, and the shift towards a digital world has had effects on society that extend far beyond the digital technology context alone (Balcerzak and Pietrzak, 2017).

All in all, according to the issues documented in the literature, we can conclude upon a positive relationship between e-commerce/m-commerce and economic growth, while contribution to decreasing unemployment by creating jobs, reducing poverty and inequality. In turn, e-commerce/m-commerce are influenced by economic growth, the level of digitalization (e.g. infrastructure and logistics), and also by the level of education.

3. Data and methodology

3.1. Data description

We used annual data starting from 2010 until 2020 (at the time of writing this research, 2020 is the latest annual data). The research is focused on the European Union's member states, divided in three clusters, depending on the level of the Gross Domestic Product (GDP) per capita expressed in purchasing power standards, as percentage of EU-27, for 2020. The first cluster contains the countries that have in 2020 GDP per capita (PPS) higher than the EU average, the second cluster contains the countries that have in 2020 GDP per capita (PPS) between 80% and 100% of the EU average and the third cluster contains the countries with the indicator below 80% of the EU average. Therefore, the three clusters are, as follows:

- Cluster 1: Luxembourg, Ireland, Denmark, Netherlands, Austria, Sweden, Germany, Belgium, Finland and France
- Cluster 2: Malta, Czech Republic, Italy, Slovenia, Cyprus, Lithuania, Spain and Estonia
- Cluster 3: Portugal, Poland, Hungary, Latvia, Romania, Slovakia, Croatia, Greece and Bulgaria.

The data source is Eurostat database (2021). Table 1 shows a list of the variables we have used in our empirical analysis. As data for m-commerce is not available, we used as a proxy a certain share of e-commerce, namely 58.9% of the rate of internet purchases by individuals in the last 3 months, which expresses the frequency of e-commerce activities. According to Loesche (2018), in 2017, the m-commerce represented 58.9% of the e-commerce activities. We have chosen this year as a benchmark in order to have a balanced view of m-commerce during the whole decade.

Table 1. Variables contained in the panel data

Variables	Description	Formulation
M-commerce	58.9% of rate of internet purchases by individuals in the last 3 months	Expressed as % of all individuals aged between 16-74 years
Internet_e	employment rate of those who are using computers with access to World Wide Web at their job from all enterprises (except financial sector)	Expressed as % of total employment
Edu	Participation rate in education and training (in the last 4 weeks)	Expressed as % of all individuals aged between 15-64 years
GDPpc	Gross domestic product per capita	Expressed in purchasing power standards (PPS) in EUR
Unemployment	Unemployment rate	Expressed as % of unemployment in active population
GINI	GINI coefficient of equivalized disposable income	Scale from 0 to 100

Table 2 shows the statistical indicators of the variables used in the panel regression model for Cluster 1. The standard deviation shows some variations in the GDP per capita because there are some differences in the Member States from Cluster 1. However, these differences are not significant, as the countries in this cluster are quite similar in terms of economic development. In terms of Gini coefficient, we can see very small differences, with a minimum of 25.1 in Netherlands in 2013 and a maximum of 34.4 in Germany in 2020. The standard deviation shows some variations in the unemployment rate, as the rate varies from 3.1% in Germany in 2019 up to 15.5% in Ireland in 2012 (influenced by the economic downturn). In terms of employment rate of those who are using computers with access to World Wide Web at the job from all enterprises (except the financial sector), there are some differences, due to digitalization. Austria reached in 2010-2011 the minimum of this indicator, while Sweden reached the maximum in 2020. The standard variations show some variations in education and m-commerce. The participation rate in education and training reached the minimum in Ireland in 2016 and the maximum in Sweden in 2019. Regarding m-commerce, Denmark in 2020 is the leader, while Belgium in 2010 is at the opposite position, showing that indeed m-commerce activities increased during the pandemic.

Table 2. Descriptive statistics of variables for Cluster 1

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
M-commerce	110	32.14	6.84	16	46.5
Internet_e	110	59	10.28	42	83
Edu	110	27.09	7.66	16.4	41.9
GDPpc	110	40156	13797	27480	81740
Unemployment	110	7.02	2.35	3.1	15.5
GINI	110	27.84	1.86	25.1	34.4

Table 3 shows the statistical indicators of the variables used in the panel regression model for Cluster 2. The standard deviation shows insignificant variations in the GDP per capita as these countries are similar in terms of economic development. In terms of Gini coefficient, we can see small differences, with a minimum of 23.4 in Slovenia in 2018 and a maximum of 37.9 in Lithuania in 2015. The standard deviation shows variations in the unemployment rate, as the rate varies from 2% in Czech Republic in 2019 up to 26.1% in Spain in 2013. In terms of employment rate of those who are using computers with access to World Wide Web at the job from all enterprises (except the financial sector), there are some differences, due to digitalization. Lithuania reached the minimum of this indicator in 2010, while Spain reached the maximum in 2020. The standard variation shows some variations in education, with a minimum in Cyprus in 2020 and a maximum in Estonia in 2019. Regarding m-commerce, the standard deviation shows quite significant variations, Czech Republic in 2020 being the leader, while Lithuania in 2010 being at the opposite position. Once again, m-commerce activities increased during the pandemic, but also during the analyzed period.

Table 3. Descriptive statistics of variables for Cluster 2

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
M-commerce	88	17.3	7.7	4.12	34.75
Internet_e	88	43	6.01	28	56
Edu	88	19.1	3.06	13.5	28
GDPpc	88	24895	3474	15380	33120
Unemployment	88	9.71	5.34	2	26.1
GINI	88	30.3	4.16	23.4	37.9

Table 4 shows the statistical indicators of the variables used in the panel regression model for Cluster 3. The standard deviation shows insignificant variations in the GDP per capita as, similar to the countries in the other clusters, the ones in Cluster 3 are similar in terms of economic development. Regarding the Gini coefficient, we can see small differences, with a minimum of 20.9 in Slovakia in 2020 and a maximum of 40.8 in Bulgaria in 2019. The standard deviation shows variations in the unemployment rate, as the rate varies from 3.2% in Poland in 2020 up to 27.5% in Greece in 2013.

Table 4. Descriptive statistics of variables for Cluster 3

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
M-commerce	99	13.04	6.93	1,18	28.86
Internet_e	99	36	6.67	20	50
Edu	99	14.66	2.58	10.7	20.6
GDPpc	99	18809	3089	11230	25350
Unemployment	99	10.65	5.43	3.2	27.5
GINI	99	31.67	4.18	20.9	40.8

In terms of employment rate of those who are using computers with access to World Wide Web at the job from all enterprises (except the financial sector), similar to the other two clusters, we find some differences, due to digitalization, as well. Bulgaria reached the minimum of this indicator in 2010, while Croatia reached the maximum in 2020. The standard variation shows some variations in education, with a minimum in Romania in 2015 and a maximum in Portugal in 2011. Regarding m-commerce, the standard deviation shows quite significant variations, Hungary in 2020 being the leader, while Romania in 2010 being at the opposite position. Once again, m-commerce activities increased during the pandemic, but also during the analyzed period.

3.2. Methodology (panel regression models)

We have examined the effects of unemployment, inequalities, education, digitalization and economic growth upon m-commerce within three different clusters of countries of the European Union, for the period 2010 – 2020. We have run a panel regression model for each cluster, using the software EViews 12.

We chose the estimation method in line with the stationarity of the data. We checked for the stationarity of the data using the following tests: Levin, Lin and Chu test (LLC), ADF- Fisher Chi-Square, and PP-Fischer Chi-Square. The null hypothesis of these tests is that the series contains a unit root. The correct order of integration is a prerequisite for regression analysis (Ali et al., 2021). A stationary time series means that it has a constant mean, variance and covariance. Non-stationary variables may lead to consequences such as (a) the forecast become meaningless, (b) difficulty in the selected of an appropriate model and (c) spurious results, even in the presence of significant t-test, F-test and high R^2 (Ali et al., 2021; Ali et al., 2020). We used the Schwarz criterion in order to select the optimal number of lags.

We examined the correlation between the variables using the correlation matrix in order to solve the problem of multicollinearity. According to Ali et al. (2021), multicollinearity is responsible for multiple consequences such as (a) inconsistent regression parameters in terms of magnitude or sign, (b) insignificant coefficients, even with high R^2 and correlation, (c) drastic changes in regression coefficients due to minor changes in data, (d) misleading conclusion due to increases in standard errors and confidence interval. Based on the results obtained, we considered the variables used in the panel regression models for the three clusters.

We applied the Estimated Generalized Least Squares (EGLS) method in the case of each cluster. We used Fixed Effects model for Cluster 2 and Cluster 3, as the result of Redundant Fixed Effects Test Likelihood Ratio indicated more consistent estimators with this model. In the case of Cluster 1, the test didn't indicate the use of fixed effects. In this respect, we applied EGLS with no effects and with Period SUR (Seemingly Unrelated Regressions) as a weighting method on the following equation:

$$\text{M-commerce}_t = a_1 \text{ M-commerce}_{t-1} + a_2 \text{ Internet\_e}_t + a_3 \text{ lnGDPpc}_{t-1} + a_4 \text{ Unemployment}_{t-1} + a_5 \text{ lnGINI}_{t-1} + c_0 + u_t$$

Where, t = 2010, 2011….2020; a_1 = coefficient of M-commerce; a_2 = coefficient of Internet_e; a_3 = coefficient of lnGDPpc; a_4 = coefficient of Unemployment; a_5 = coefficient of lnGINI; c_0 = constant; u_t = error term

Period SUR corrects for heteroskedasticity and general correlation of observations within a cross-section (EViews, 2021). This method cannot be applied with fixed effects. Even if the challenge of heterogeneity is not addressed, the problems would have been bigger in the case of applying fixed effects (Frățilă et al., 2021).

With respect to Cluster 2 and Cluster 3, we applied EGLS with fixed effects, weighted by Cross-section SUR option and White cross-section coefficients covariance method on the following equations:

Cluster 2:

$$\text{M-commerce}_t = a_1 \text{ M-commerce}_{t-1} + a_2 \text{ Internet\_e}_t + a_3 \text{ lnGDPpc}_{t-1} + a_4 \text{ Unemployment}_t + a_5 \text{ lnGINI}_{t-1} + c_0 + u_t$$

Where, t = 2010, 2011….2020; a_1 = coefficient of M-commerce; a_2 = coefficient of Internet_e; a_3 = coefficient of lnGDPpc; a_4 = coefficient of Unemployment; a_5 = coefficient of lnGINI; c_0 = constant; u_t = error term

Cluster 3:

$\text{M-commerce}_t = a_1\ \text{M-commerce}_{t-1} + a_2\ \text{Edu}_{t-1} + a_3\ \text{lnGDPpc}_{t-1} + a_4\ \text{Unemployment}_{t-1} + a_5\ \text{lnGINI}_{t-1} + c_0 + u_t$

Where, t = 2010, 2011….2020; a_1 = coefficient of M-commerce; a_2 = coefficient of Edu; a_3 = coefficient of lnGDPpc; a_4 = coefficient of Unemployment; a_5 = coefficient of lnGINI; c_0 = constant; u_t = error term

The Cross-section SUR option allows for contemporaneous correlation between cross-sections (clustering by period), estimating a feasible GLS specification correcting for heteroskedasticity and contemporaneous correlation (EViews, 2021). We used White cross-section (period cluster) for one-way period clustering.

The main benefit of fixed effects estimations is that the potential sources of biases in the estimations are limited in comparison to classical ordinary least squares models (Collischon and Eberl, 2020). According to the aforementioned authors, in the case of ordinary least squares models, a correlation between any unobserved variable and the outcome or the treatment variable of interest results in a biased estimate of the treatment effect. In contrast, fixed effects models limit the sources of bias to time-varying variables that correlate with the treatment as well as with the outcome over time (Collischon and Eberl, 2020). According to Collischon and Eberl (2020), this condition is far more achievable than the strong exogeneity assumption of ordinary least squares models. A detailed methodology of fixed effects models can be seen in Brüderl and Ludwig (2015).

We applied logarithmic transformation for GDPpc and GINI coefficient to ensure that the estimates coefficients are robust to the measurement units of the variables (Frățilă et al., 2021; Mudronja et al., 2020).

In order to verify the maximum likelihood of the estimators, we used the following tests, after the estimation of the models' results (Frățilă et al., 2021):

- Model validity: Fischer test was used (probability < 5%).
- Significance of estimators: checking of their associated probability (probability < 5%).
- Absence of multicollinearity: correlation matrix.
- The existence of non-zero standard errors, but not much different from zero.
- Absence of dependence between cross sections (probability >5%): Breusch Pagan LM and Pesaran CD. The null hypothesis shows the absence of cross-sectional dependence in the panel (Ali et al., 2021). Cross-sectional dependence means that a disturbance in one economy certainly transfers to other economies (Destek and Aslan, 2017) due to globalization, cross-country linkages and economic integration in the world (Ali et al., 2021). If it is ignored, it may lead to invalid test

statistics and efficiency loss (Ali et al., 2021). According to the same authors, Breusch Pagan LM is applicable for panels having small-cross sections and large time period.

- Jarque Berra test to check if the residuals are normally distributed (probability >5%).
- Linearity of the model: R-squared (coefficient of determination).

4. Results

As we mentioned in the previous section, we have examined the effects of unemployment, inequalities, education, digitalization and economic growth upon m-commerce within three different clusters of countries of the European Union, for the period 2010 – 2020. First, we tested the stationarity of data. Table 5 summarizes the outcome of the panel unit root tests. As can be observed, the majority of the variables are stationary in the first difference, while the others are in level.

Table 5. Panel unit root tests output

Variable	**First difference - Cluster 1**		
	LLC	**ADF**	**PP**
M-commerce	-3.95255***	51.2772***	60.5513***
Internet_e	-5.79913***	57.0247***	62.3660***
lnGDPpc	-5.79099***	58.2529***	59.2721***
Unemployment^	-2.83959***	33.2631**	33.4288**
lnGINI	-12.1954***	120.027***	117.774***
Variable	**First difference – Cluster 2**		
	LLC	**ADF**	**PP**
M-commerce	-2.06794***	26.3458**	33.8405***
Internet_e	-4.25941***	46.0500***	46.1776***
lnGDPpc	-4.55149***	38.8847***	37.3577***
Unemployment^	-2.71742***	29.0140**	45.5389***
lnGINI	-9.21121***	83.7675***	84.5817***
Variable	**First difference – Cluster 3**		
	LLC	**ADF**	**PP**
M-commerce	-3.96881***	32.1085**	37.5460***
Edu	-9.25234***	89.6145***	102.024***
lnGDPpc	-4.74158***	47.5942***	48.0818***
Unemployment^	-4.89980***	45.1194***	45.3761***
lnGINI	-6.01388***	63.6696***	107.058***

Notes: ^ level ; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Lag lengths are determined via Schwarz Info Criterion.

Then we examined the correlation between the variables using the correlation matrix in order to solve the problem of multicollinearity. Table 6 shows the correlation coefficients of the variables.

Table 6. Correlation matrix

Cluster 1	**M-commerce**	**Internet_e**	**Edu**	**lnGDPpc**	**Unemployment**	**lnGINI**
M-commerce	1					
Internet_e	0.5554	1				
Edu	0.5366	0.7840	1			
lnGDPpc	0.3376	-0.2407	-0.0299	1		
Unemployment	-0.5470	-0.1522	-0.0972	-0.3407	1	
lnGINI	0.0311	-0.5329	-0.4435	0.3236	0.1406	1
Cluster 2	**M-commerce**	**Internet_e**	**Edu**	**lnGDPpc**	**Unemployment**	**lnGINI**
M-commerce	1					
Internet_e	0.6088	1				
Edu	0.1696	0.3116	1			
lnGDPpc	0.4763	0.4455	-0.4042	1		
Unemployment	-0.3961	0.0528	-0.0421	-0.1656	1	
lnGINI	-0.1601	-0.0299	-0.2437	-0.1224	0.5249	1
Cluster 3	**M-commerce**	**Internet_e**	**Edu**	**lnGDPpc**	**Unemployment**	**lnGINI**
M-commerce	1					
Internet_e	0.8179	1				
Edu	0.2676	0.3558	1			
lnGDPpc	0.7328	0.6797	0.4664	1		
Unemployment	-0.1364	0.0273	0.1682	-0.0851	1	
lnGINI	-0.5897	-0.4290	-0.0728	-0.400	0.1205	1

A positive or a negative correlation that is greater than 0.8 serves as a threshold for a correlation presence (Mudronja et al., 2020; Lovrić, 2005). The review of the correlation coefficients shows that there are strong linear associations between employment rate of those who are using computers with access to World Wide Web at their job from all enterprises and m-commerce in the case of Cluster 3. An approximate value of 0.8 is found between the participation rate in education and training in the last 4 weeks and employment rate of those who are using computers with access to World Wide Web at their job from all enterprise in the case of Cluster 1. In these conditions, we solved the issue of multicollinearity by eliminating one of the variables from the panel regression models.

Following the estimation of the models, the results are described in Table 7. We obtained robust and significant coefficients, as their specific probability is less than 5%. The selected variables are representative for m-commerce, as we obtained high values of R-squared. We used Fixed Effects for Cluster 2 and Cluster 3, but not for Cluster 1, as the results of Redundant Fixed Effects Test Likelihood Ratio indicated so.

In line with previous studies, our empirical results provide support for a positive relationship between m-commerce and economic growth (Yurtkur and Bahtyiar, 2020), m-commerce and digitalization (Afonasova et al., 2019), but also between m-commerce and education (Luo and Niu, 2019;). Economic growth seems to have a greater impact for least developed countries. As a consequence, the impact of economic growth upon m-commerce is highest in the case of Cluster 3, followed by Cluster 2 and then Cluster 1. This could be considered normal, as less developed countries usually register higher economic growth rates, within their convergence process towards higher GDP and better living conditions.

As regards the positive relationship between m-commerce and digitalization, we obtained that an increase of 10 percentage points of the employment rate of those who use computers with access to World Wide Web at their job (from all enterprises except financial sector) will generate an increase of 0.9% of the m-commerce in the case of Cluster 1 and an increase of 1.3% of m-commerce in the case of Cluster 2. In this respect, we see that for Cluster 2 the impact on m-commerce is a little bit higher than for Cluster 1, which may have been influenced by the fact that the indicator used does not take into account the employees in the financial sector, while the countries in the first cluster do have better developed financial sectors, employing a lot of people.

In the case of Cluster 3, this indicator was eliminated as it is highly correlated with education. As a consequence, for Cluster 3, an increase of 10 percentage points in the participation rate in education and training in the last 4 weeks (lagged one year) generates an increase of 2.9% of m-commerce. As we can see, education is important for m-commerce, as poor education skills may negatively influence the ability of consumers to conduct online purchases.

Table 7. Results of the panel regression models

	Cluster 1	**Cluster 2**	**Cluster 3**
	M-commerce	M-commerce	M-commerce
L.M-commerce	0.8049*** (0.0427)	0.8521*** (0.0354)	0.8223*** (0.0538)
Internet_e	0.0969*** (0.0248)	0.1323*** (0.0267)	
Edu			0.2938*** (0.0612)
lnGDPpc	1.5589*** (0.4484)	2.6522*** (0.6022)	9.4697*** (1.4955)

Unemployment	-0.1633*** (0.0659)	-0.1746*** (0.0502)	-0.0343*** (0.0120)
lnGINI	7.5115** (3.1338)	-3.7273** (1.2134)	-8.5439*** (0.7616)
Constant	-39.0901*** (12.2539)	-13.9912* (7.6120)	-63.6387*** (13.2706)
R^2	0.9569	0.9571	0.9880
Fixed Effects	no	yes	yes
Jarque -Bera (p-value)	0.9162	0.3167	0.9636
Breusch Pagan LM (p-value)	0.4510	0.9527	0.9366
Pesaran CD (p-value)	0.9577	0.6093	0.8332
Observations	100	80	90
Number of countries	10	8	9

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors in parentheses.

Our results indicate a negative relationship between unemployment and m-commerce, as the larger the unemployment is, the lower the income of the population, which in turn affect population consumption and also online purchases. In this respect, an increase of 10 percentage points of the unemployment rate (lagged one year) generates a decrease of 1.6% of m-commerce in the case of Cluster 1 and a reduction of 0.3% in the case of Cluster 3. For Cluster 2, an increase of 10 percentage points of the unemployment rate generates a decrease of 1.7% of m-commerce.

Regarding income inequalities, the results are quite different across the three clusters. We obtained a negative relationship between income inequalities and m-commerce for Cluster 2 and Cluster 3, which can be explained by the fact that inequalities are usually larger in least developed countries, where poverty rates are higher. Therefore, the higher the poverty and income inequalities, the lower the m-commerce activities. On the other hand, the results show a positive relationship in the case of Cluster 1, which consists of the richest and most developed countries. This means that for those countries, the higher the inequalities, the higher the m-commerce and such a relationship may be explained by the fact that rich people might have quite different shopping habits, relying to a greater extent on m-commerce.

Tests for normal residuals' distribution, and the absence of dependence between cross-sections are shown in the previous table. According to the Jarque–Bera test, the residuals are normally distributed. A *p*-value greater than 0.05 confirms the null hypothesis of the test, which claims that the residuals are normally distributed. Breusch Pagan LM and Pesaran CD reveal there is no dependence between cross-sections in none of the three panel regression models.

Their *p*-value is greater than 0.05 and confirms the null hypothesis, which claims the absence of dependence between cross-sections.

5. Conclusions

Our paper assesses the relationship between m-commerce and digitalization, education, economic growth, unemployment and income inequalities within three different clusters of countries of the European Union, for the period 2010 – 2020, using panel date regression models. We selected the three clusters depending on the level of the Gross Domestic Product (GDP) per capita expressed in purchasing power standards, as percentage of EU-27, for 2020. We believe that this is an appropriate indicator for assessing the degree of development and living standards within the EU countries, which are important for our research, as they highly influence the way people conduct their shopping activities and also their shopping preferences and habits.

Our results confirm a positive relationship between m-commerce and digitalization, education and economic growth, while showing a negative link between m-commerce and unemployment in all clusters. High rates of economic growth promote convergence and economic development, and above these, they foster private consumption. Moreover, education and digital skills offer population the needed information and abilities for conducting online activities, including m-commerce. Therefore, m-commerce is fostered by economic growth, education and digital skills.

On the other hand, our empirical analysis concludes upon quite different results across the three clusters, when considering the relationship between m-commerce and income inequalities. We obtained a negative relationship between income inequalities and m-commerce for Cluster 2 and Cluster 3, and a positive one for Cluster 1. We link these results with the fact that inequalities are usually larger in least developed countries, where poverty rates are higher, and consequently private consumption is lower, education and digital skills are less developed, affecting m-commerce activities. On the other hand, in highly developed countries, where the living standards are very high, rich people might have quite different shopping habits, relying mainly on m-commerce.

Our results are important as they offer a macroeconomic perspective of the main factors that influence m-commerce. To the best of our knowledge, the literature is rather scarce in this respect, so that our paper contributes to its enrichment.

The main limitation of our research consists in determining the appropriate data for m-commerce, as the main databases of the international institutions contain mainly data regarding e-commerce, given the fact that the difference between the two is rather thin. Plus, we used proxies for digitalization and education: employment rate of those who are using computers with access to World Wide Web at their job from all enterprises, except financial sector and the participation rate in education and training in the last 4 weeks. Another limitation could be the fact that we had to use annual data (as data with a higher frequency were not available) and, as a consequence, we had to run the models on a relatively reduced data sample, with observations ranging between 80 and 100.

Future works in this area could tackle in detail the channels of influence from the macroeconomic indicators upon m-commerce and also policies through which the government could foster m-commerce/e-commerce activities, in order to enhance firm efficiency and foster productivity, with the aim of promoting a digital development of the economy.

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