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Determinants of Digital Payment Intensity in the MENA Region: A Panel Data Analysis

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ABSTRACT. The rise of digital payments, particularly during the 2020 lockdown, underscores the growing significance of fintech, valued at over USD 127 billion globally. However, studies on factors influencing digital payment utilization remain limited. This study analyzes determinants of digital payment intensity in the MENA region, using data from 13 countries (2011-2021) sourced from the World Bank. Panel data analysis revealed that the percentage of accounts and deposits in financial institutions positively impacts digital payments, while household savings negatively influence them. Conversely, digital payments received are positively affected by accounts, deposits, retirement savings, and borrowing levels, but negatively influenced by household savings and entrepreneurial savings. The study concluded that the factors affecting digital payments received are both cross-sectional and time-fixed, while those affecting payments made are random.

1. Introduction

The landscape of financial literature studies in recent years has concentrated on the financial sector's digital transformation. The innovations in financial technology to better facilitate payments and intercontinental commercial transactions [1] have made settling payments affordable, accessible, and more convenient [2] had stirred the interest of both academics and practitioners. Modern technologies propel economies toward digitalization and

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the transformation of payment systems. As Löber and Houben [3] highlighted, the clogs in domestic and international legacy payment systems that result in high costs, restricted access, slow speeds, and lack of transparency are gradually being eliminated by technology developments.

However, Mavlutova et al. [4] argued that using financial technology such as digital payment systems not only lower transaction costs but also paves the way to better alternatives in banking and finance, transformed value chains, and even business models. For example, AlHares et al. [5] reported that financial technology and digital payment systems offer various innovative financial products and services that challenge traditional banking. They compete with banks in similar market sectors and enterprises, but they serve a broader client base and offer easy-to-access financial services.

Despite the noted prominence and impact of digital payment usage, Eling and Lehmann [6] and Pramanik et al. [7] observed that the number of empirical research on the factors influencing digital transformation and intensity is still much to be desired. This inadequacy creates a myopic perspective of digital payment systems, undermining their critical role in sustainable economic development [8], especially in countries and regions heavily reliant on banking systems.

With this thought in mind, Arezki and Senbet [9] described that most MENA region countries are "overwhelmingly bank-based." They contend that this is due to governments' significant economic influence, resulting in two business categories. The first category consists of big businesses with bank connections, frequently owned by states. In contrast, the second category is composed of Small and medium-sized businesses (SMEs) that struggle to borrow capital since they have poor access to banks and rely primarily on unofficial financing and retained earnings. This unique financial inclusion state and SME financing structure of the MENA region makes it an ideal beneficiary of the earlier-mentioned effects of financial technology and digital payment transformation. Nevertheless, Lukonga [10] reported that the economic significance of payment systems and crowdfunding in MENA remains modest despite being the region's two most dominant fintech developments. From this perspective, it can be deduced that although the utilization of digital payment systems in MENA countries has grown and succeeded, further understanding of its determining factors may amplify its role in sustaining the region's economic development.

Thus, this study intends to close the knowledge gap by employing empirical research to evaluate the determinants of digital payment intensity in the MENA region using panel data analysis. Specifically, the study investigates how financial inclusion and entrepreneurial financing indicators could influence the use of digital payments in the region. The contribution of this paper could be highlighted in two folds. First, identifying economic and financial determinants of digital payment intensity would aid in developing a holistic economic and financial policy that would take advantage of financial technology like digital payment systems to address sustainable development. Secondly, the study results will be helpful for organizations who want to maximize their digital payment platforms to widen their reach to their customers and create business models that offer greater economic value.

2. Hypothesis Development

Digital Payment System in the MENA Region

Allen [11] highlighted that one of its noteworthy characteristics is the variety of countries that make up the MENA area in terms of GDP per capita in purchasing power parity (PPP) terms. Yemen, which has one of the lowest per capita incomes in the world, is at one end of the income spectrum, while Qatar, which has one of the highest, is at the other. A wide variety exists in the middle, leading to extreme variations of financial and technological development and agenda across countries.

For example, Santosdiaz [12] reported that the Kingdom of Saudi Arabia is going through substantial economic growth changes focused on its national economic development policy, known as Saudi Vision 2030. As a result, some aspects—like its financial services sector and general digital shift—have received attention.

In addition, MENA nations, including Kuwait, have implemented economic growth plans in recent years [5]. The Kuwait Vision 2035 plan will work to diversify Kuwait's economy and help the country reduce its reliance on oil, which has fueled economic growth in Kuwait and its GCC neighbors for the majority of the past century and continues to do so now.

Moreover, Zarrouk et al. [13] indicated that Middle Eastern FinTech is expanding fast. According to a February 1 statement by UAE lender Mashreq, citing Middle East Institute data, more than 800 FinTech companies in payments, insuretech, and cyber security are expected to raise more than $2 billion in venture capital funding by 2022. The UAE Digital Economy Strategy intends to boost the digital economy's 10% proportion of GDP to 20% over the next decade.

Financial Inclusion and Digital Payment Intensity

According to the World Bank [14], financial inclusion is "people and businesses having access to useful and reasonably priced financial products and services that meet their needs—transactions, payments, savings, credit, and insurance—delivered responsibly and sustainably." Sun (2018) reported that financial inclusion is a cornerstone of a fair, equal society and a thriving economy. Economic development can significantly increase the use of new technology that can help to increase access to affordable financial goods and services outside conventional platforms.

In addition, Carranza et al. [15] also suggested that financial inclusion through e-banking influence clients to choose financial services because of perceived ease- of- use and perceived usefulness—this availability of increases the use of digital payment systems resulting in balanced, sustainable development in the financial system.

In another study, Allen et al. [11] examined how financial inclusion activities devised by banking services targeting low-income and less-educated customers and underserved regions have significantly impacted household access to digital payment systems. They concluded that a successful business model that solves the financial access problem could provide real growth in many countries.

Finally, Ahamed and Mallick [16] argue that digitalization supports value creation and found a positive association between customer deposit funding share and the lower marginal cost. With this, the research set the first two hypotheses;

H_1: Financial Inclusion indicators significantly determine the Digital Payment Intensity in the MENA Region regarding Digital Payments Made.

H_2: Financial Inclusion indicators significantly determine the Digital Payment Intensity in the MENA Region regarding Digital Payments Received.

Entrepreneurial Financing and Digital Payment Intensity

There is proof that SMEs turned down for loans by banks can frequently get it later on via fintech platforms. This is true for various nations, making it significant for nations in the MENA Region [11]. Due to their rapid growth in emerging nations, Huang et al. [17] reported that important FinTech innovations had attracted much attention in recent years. China is the nation where the most P2P loan transactions worldwide were made in 2017, with a total value of almost

$550 billion. P2P lending's main benefit is that it does away with the necessity for the traditional banking system by making it easier for lenders and borrowers to find one another through an online marketplace intensifying the use of digital payment systems.

Finally, Jagtiani and Lemieux [18] compare interest rates charged with the interest rate borrowers would have to pay by holding a credit card balance using loan-level data from a unique lending platform. They discover that some individuals with low credit ratings have obtained credit at significantly lower rates because of the usage of alternative data. The shift to more accessible financing options provided by fintech innovations influences the utilization of the accompanying digital payment systems. Thus, the following hypotheses are established;

H_3: Entrepreneurial Financing indicators significantly determine the Digital Payment Intensity in the MENA Region regarding Digital Payments Made.

H_4: Entrepreneurial Financing indicators significantly determine the Digital Payment Intensity in the MENA Region regarding Digital Payments Received.

3. Methods

The data analyzed were extracted from the World Bank Open Data source covering 2011 to 2021. Only MENA countries with sufficient observations across three variables (financial inclusion, entrepreneurial financing, and digital payment intensity) were utilized in the study. Only 13 MENA countries qualified for the analysis, including Algeria, Bahrain, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Morocco, Saudi Arabia, Tunisia, and the United Arab Emirates. Table 1 shows the indicators for financial inclusion, entrepreneurial financing, and digital payment intensity utilized in the study;

Table 1. Variables Used in the Study

Variable	Explanation (Based on the World Bank Definition)
Digital Payment Intensity	
MDP	Made a digital payment (% age 15+). The percentage of respondents who report using mobile money, a debit or credit card, or a mobile phone to make a payment from an account--or report using the internet to pay bills or to buy something online or in a store--in the past year.
RDP	Received digital payments (% age 15+). The percentage of respondents who report using mobile money, a debit or credit card, or a mobile phone to receive payment from an account--or report using the internet to pay bills or to buy something online or in a store--in the past year.

Financial Inclusion	
ACC	Account (% age 15+). Denotes the percentage of respondents who report having an account (by themselves or together with someone else).
DEP	Made a deposit (% with a financial institution account, age 15+). The percentage of respondents with a financial institution account report making one or more deposits into their account in the past year. This includes cash, electronic deposits, or any money transfer by the respondent, an employer, or another person or institution into the account.
SAV	Saved any money (% age 15+) The percentage of respondents who report personally saving or setting aside any money for any reason and using any mode of saving in the past year.
SAO	Saved at a financial institution (% age 15+) The percentage of respondents who report saving or setting aside any money at a bank or another type of financial institution in the past year.
SFOA	Saved for old age (% age 15+) The percentage of respondents who report saving or setting aside any money in the past year for old age.
BOR	Borrowed any money (% age 15+) The percentage of respondents who report borrowing any money (by themselves or together with someone else) for any reason and from any source in the past year.
Entrepreneurial Financing	
SOEFB	Saved to start, operate, or expand a farm or business (% age 15+) The percentage of respondents who report saving or setting aside any money in the past year to start, operate, or expand a farm or business.
BOEFB	Borrowed to start, operate, or expand a farm or business (% age 15+) The percentage of respondents who report borrowing any money to start, operate, or expand a farm or business in the past year.

Moreover, Panel Data Analysis was used to examine how financial inclusion and entrepreneurial financing affect the digital payment intensity of a country. Singh [19] noted that panel data are superior to cross-section and time series analysis since reliable estimates could be derived with less restrictive assumptions. Additionally, the model considers individual heterogeneity, resulting in estimate effects that are indiscernible in pure cross-sectional or pure time-series data. The study used both a fixed effect and a random effect model as a methodological choice, but the application of the Hausman test specification allowed for the selection of the superior model. The consequent interpretation was solely based on the identified superior model. The model specifications analyzed in the study are presented below;

$$MDP_{jt} = \beta_{0j} + \beta_1 ACC_{jt} + \beta_2 DEP_{jt} + \beta_3 SAV_{jt} + \beta_4 SAO_{jt} + \beta_5 SFAO_{jt} + \beta_6 BOR_{jt} + \beta_7 SOEFB_{jt} + \beta_8 BOEFB_{jt} + \mu_{jt} \quad \text{(Eq.1)}$$

$$RDP_{jt} = \beta_{0j} + \beta_1 ACC_{jt} + \beta_2 DEP_{jt} + \beta_3 SAV_{jt} + \beta_4 SAO_{jt} + \beta_5 SFAO_{jt} + \beta_6 BOR_{jt} + \beta_7 SOEFB_{jt} + \beta_8 BOEFB_{jt} + \mu_{jt} \quad \text{(Eq.2)}$$

Equations 1 and 2 are the fixed effect model tested in the study where MDPjt and RDPjt are the indicators of digital payment intensity for country j in year t; β0 is a common y-intercept; ACC, DEP, SAV, SAO, SFAO, and BOR represent the financial inclusion indicators while SOEFB and BOEFB are the entrepreneurial financing indicators; εjt is the stochastic error term of firm j at time t; β1 to β8 are coefficients of the concerned explanatory variables. Additionally, equations 3 and 4 are the random effects version of the same models adding μjt as the error term of country j at time t.

$$MDP_{jt} = \beta_{0j} + \beta_1 ACC_{jt} + \beta_2 DEP_{jt} + \beta_3 SAV_{jt} + \beta_4 SAO_{jt} + \beta_5 SFAO_{jt} + \beta_6 BOR_{jt} + \beta_7 SOEFB_{jt} + \beta_8 BOEFB_{jt} + \varepsilon_{jt} + \mu_{jt} \quad \text{(Eq.3)}$$

$$RDP_{jt} = \beta_{0j} + \beta_1 ACC_{jt} + \beta_2 DEP_{jt} + \beta_3 SAV_{jt} + \beta_4 SAO_{jt} + \beta_5 SFAO_{jt} + \beta_6 BOR_{jt} + \beta_7 SOEFB_{jt} + \beta_8 BOEFB_{jt} + \varepsilon_{jt} + \mu_{jt} \quad \text{(Eq.4)}$$

4. Results

The data utilized in this study include the digital payments intensity as dependent variables (MDP = Made a digital payment, % age 15 and RDP = Received digital payments, % age 15). On the other hand, explanatory variables include financial inclusion (ACC = Account% age 15+, DEP = Made a deposit % with a financial institution account age 15+, SAV = Saved any money % age 15+, SAO = Saved at a financial institution % age 15+, SFOA = Saved for old age % age 15 +, and BOR = Borrowed any money % age 15 +) and entrepreneurial financing (SOEFB = saved to start, operate, or expand a farm or business and BOEFB = Borrowed to start to operate or expand a farm or business) indicators.

Table 2. Descriptive Statistics

Variable (%)	Obs	Mean	Std. Dev.	Min	Max
MDP	143	40.237	29.953	5.9	87.13
RDP	143	35.507	26.076	13.07	84.54
ACC	143	56.67	27.519	9.72	93.98
DEP	143	67.475	20.501	11.2	112.217
SAV	143	45.791	14.076	13.27	76.31
SAO	143	18.994	13.654	.69	59.35
SFOA	143	14.701	10.073	7.49	46.16
BOR	143	53.624	18.349	18.54	95.48
SOEFB	143	12.396	6.725	1.08	32.087
BOEFB	143	6.171	4.491	2.62	29.913

Table 2 summarizes descriptive statistics of the 143 observations of each variable included in the study. The data covers the periods from 2011 to 2021. The same table shows that the mean and standard deviation of the percentage of digital payments made (x=40.237, SD=29.953) are more significant than the mean percentage of digital payments received (x=35.507, SD = 26.076). Regarding financial inclusion variables, the % of people who deposited with a financial institution has the highest mean (x=67.475, SD=20.501). In contrast, the percentage of individuals saving money for old age has the lowest mean (x=14.701, SD=10.073). Finally, regarding entrepreneurial financing indicators, the % of people saving money to start operating or expand a farm or business is significantly higher, with a mean of 12.396 (SD=6.725) compared to those who borrowed to do the same (x=6.171, SD=4.491).

Table 3. Pairwise correlations

Variables (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) MDP	1.000									
(2) RDP	0.896*	1.000								
(3) ACC	0.969*	0.901*	1.000							
(4) DEP	0.591*	0.663*	0.636*	1.000						
(5) SAV	0.591*	0.493*	0.574*	0.348*	1.000					
(6) SAO	0.834*	0.813*	0.826*	0.673*	0.704*	1.000				
(7) SFOA	0.681*	0.604*	0.621*	0.388*	0.794*	0.802*	1.000			
(8) BOR	0.628*	0.583*	0.560*	-0.007	0.642*	0.588*	0.598*	1.000		
(9) SOEFB	0.534*	0.347*	0.524*	0.106	0.753*	0.574*	0.769*	0.553*	1.000	
(10) BOEFB	0.231*	0.079	0.197*	-0.182*	0.269*	0.095	0.225*	0.361*	0.494*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

All study variables are significantly correlated except DEP and the entrepreneurial financing indicators, as shown in Table 2. All observed correlations are only significant at the 10% level, as observed from the same table. The highest correlation can be observed between the digital payment's intensity variables (MDP and RDP), and the % of depositing with a financial institution has the highest mean (ACC), consistent with the intuition that most of these digital transactions may have gone through the active participation of the sample country's financial institutions.

A. Model Specification for Digital Payments Made (MDP)

We evaluate Random versus Fixed Effects models to determine the best model to address the issue of heteroskedasticity and serial correlation. The Hausman specification test determines the particular effects' character to conduct this comparison [20]. By contrasting the set with random effects, the Hausman test chooses a more effective model over an ineffective model [19]. The preferred model for the test is random effects, and the recommended model for the alternative hypothesis is fixed effects. The results of the panel data analysis for MDP using both fixed and random effects and the corresponding Hausman specification test outputs are shown in Table 3.

Table 4. Panel Data Analysis Results for MDP

MDP	Fixed Effects	Random Effects
ACC	.522***	.687***
DEP	.121***	.066
SAV	-.124*	-.126*
SAO	-.101	-.003
SFOA	.37***	.50***
BOR	-.132**	-.039
SOEFB	.18	-.14
BOEFB	-.168	.021
Constant	10.551***	-1.075
F-test	52.122***	
Wald chi^2		486.714***
Hausman Test	7.053 (p-value = 0.531)	

*Dependent Variable: MDP, *** p<.01, ** p<.05, * p<.1*

Looking at the results in Table 3, both Fixed Effects and Random Effects models are statistically significant in explaining the level of MDP at the 1% level with large F-test or Wald Chi values of 52.122 and 486.714, respectively. In the case of the fixed effect model, ACC, DEP, and SFOA positively influence MDP, while SAV and BOR negatively influence the same. The Fixed effect model showed five significant explanatory financial inclusion variables, with no entrepreneurial financing variable found to have a statistically significant effect on MDP.

On the other hand, the random effects model resulted in two highly positive significant loading factors (ACC and SFOA) and one negatively significant loading factor (SAV), all of which are financial inclusion indicators. However, the Hausman Test specification should be considered to identify which model possesses the most reliable estimators considering the heteroskedasticity, serial correlation, and heterogeneity of the variables of interest. The Hausman test yielded a small, non-statistically significant chi value of 7.053 (p=0.531). Thus, there is insufficient evidence to reject the null hypothesis that the random effects model is the most suitable panel data technique for the dataset.

This result would explain why the coefficients of the significant causal variables ACC, SAV, and SFOA are lesser in the fixed effect model compared to the fixed effect coefficients of the same variables. The non-significant correlation between cross-section-specific error terms of the model and the regressors resulted in an underestimation of the coefficients of the significant variables in the fixed effect model [21]. Further analysis, therefore, should solely be based on the random effects model as evidence supports that some factors that affect MDP vary randomly across countries.

The random effects model estimates in Table 9 show that one unit increase in accounts created in financial institutions (ACC) results in a 68.7% increase in digital payments. In addition, one unit of increase in % of saved money for old age (SFOA) yields a 37% increase in the MDP. ACC has the greatest influence on MDP among all significant financial inclusion variables. On the other hand, SAV negatively influences MDP - a unit increase in SAV results in a 12.6% decrease in MDP.

B. Model Specification for Digital Payments Received (RDP)

Table 5. Panel Data Analysis Results for RDP

RDP	Fixed Effects	Random Effects
ACC	.277**	.584***
DEP	.563***	.395***
SAV	-.71***	-.383***
SAO	.024	-.132
SFOA	1.058***	.697***
BOR	.91***	.55***
SOEFB	-1.101***	-.882***
BOEFB	-.216	-.117
Constant	-35.53***	-32.332***
F-test	37.363***	
Wald chi^2		1114.199***
Hausman Test	21.888 (p-value = 0.005)	

*Dependent Variable: RDP, *** p<.01, ** p<.05, * p<.1*

Table 4 shows the Fixed and Random Effects models for RDP. As seen from the table, both models are also statistically significant in explaining the level of RDP at the 1% level with large F-test or Wald Chi values of 37.363 and 1114.199, respectively. Both models found ACC, DEP, SAV, SFOA, BOR, and SOEFB statistically significant at the 1% level with the exemption of ACC, which was only significant at the 5% in the fixed effect model. Consequently, the Hausman Test specification results yielded a chi value of 21.88 (p=0.005), suggesting that the random effects model does not yield a reliable estimate for this dataset. This statistic would mean that there is an observed significant correlation between cross-section-specific error terms of the model and the regressors, which resulted in the possible inaccuracy of estimates in the random effects model.

With this, the appropriate model (fixed effect) shows that one unit increase in ACC, DEP, SFOA, and BOR results in a 27.7%, 56.3%, 105.8%, and 91% increase in RDP, respectively. The fixed effect model proves that among the identified significant explanatory variables of RDP, SFOA has the most substantial positive impact. In contrast, a unit increase in SAV and SOEFB results in a 71% and 110.1% decrease in RDP, respectively. The entrepreneurial financing indicator SOEFB tends to have the most influential variable in causing a decline in digital payments intensity regarding RDP. These observed effects are cross and time fixed and not random.

5. Conclusion

Adopting and implementing digital technology is a complex process that involves altering customer experiences, value propositions, and business models to enhance the efficiency of the financial sectors. Liu et al. [22] reasoned that digitalization transformation is not conceivable without adopting various technologies in the financial sector. The study aimed to further the understanding of digital financial systems by exploring the factors that will drive their usage or intensity.

The study found that financial inclusion indicators significantly influence digital payment intensity. The results proved that number of individuals who report having an account significantly increases the volume of digital payments made. In addition, the amount of saved money for retirement also influences the volume of digital payments made. This finding is consistent with the findings of Carranza et al. [15], who suggested that increased interaction with banks through e-banking increases the use of digital payment systems. On the other hand, the study also found that the decrease in savings outside financial institutions could increase digital payment intensity, particularly digital payments made. Mavlutova et al. [4] offered one possible explanation: adopting new technologies in the financial sector results in increased access to goods and services through better and more convenient delivery channels that entice the use of digital payment systems that comes with it. Moreover, the study also proves that the effect of financial inclusion on the volume of digital payments made is random.

Furthermore, the study found that financial indicators related to the number of accounts opened, deposits made, and borrowings from financial institutions significantly increases the digital payment intensity in received payments. These findings would support the claim of Allen [11] that financial institutions' adoption of digital banking systems made their services more accessible to a broader consumer base. These actions, in effect, result in more funds received by consumers from formal institutions through digital payment systems. On the other hand, the negative association between savings for entrepreneurial financing and digital payments received may suggest an increased utilization of access to alternative sources of capital outside formal financial institutions. Jagtiani and Lemieux [18] hinted that some individuals with low credit ratings could obtain credit at significantly lower rates because of more accessible financing options outside fintech innovations or the formal banking system. This observation calls for further strengthening regulations for informal lending and lending through financial technology startups.

Finally, future studies could improve the current findings by comparing the tested models in different regions. This process would allow a more comprehensive perspective of the critical role of digital payment systems and their determinants in achieving regional and national economic sustainability.

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