

Digital Financial Exclusion in the EU: Socio-Economic Determinants and Inclusion Effects

Research Paper

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Abstract: **Research purpose.** This paper examines the potential of digital financial services to increase financial inclusion. It analyses socio-economic factors associated with the adoption of basic and advanced digital options. By distinguishing between levels of digital engagement, the study clarifies whether digitalisation is associated with broader access to finance or serves as an additional benefit for already advantaged groups.

Design / Methodology / Approach. Using micro-level data from the Flash Eurobarometer 509 for EU countries, the study employs logistic and probit regression models. These methods are used to examine potential socio-economic factors of digital financial service adoption and to evaluate whether their use is associated with financial inclusion or exclusion. The empirical approach allows us to compare basic services, such as mobile banking and digital payments, with more advanced tools, including digital investments. In addition, robustness checks and alternative model specifications are employed to compare the results across different measures of financial inclusion.

Findings. The results show that digital financial services vary widely by socio-economic group. Older people, those with lower levels of education, and the economically inactive are more likely to experience digital financial exclusion. These patterns suggest that digital finance is shaped by existing socio-economic structures, rather than being universally accessible. While basic digital services are linked to significantly lower exclusion, advanced options are mostly used by already advantaged groups. This means digital finance may help with basic financial inclusion but may further reinforce disparities at higher levels.

Originality / Value / Practical implications. By linking digital financial service adoption to financial inclusion outcomes, the study provides new empirical evidence on the limits of digitalisation as an inclusion strategy. Unlike much of the existing literature, it jointly examines both the factors associated with its adoption and the consequences for financial inclusion. The results suggest that policies should focus not only on expanding digital financial technologies but also on reducing socio-economic barriers that shape their use. Attention needs to be paid to digital skills, financial literacy, and access to digital infrastructure. Such targeted approaches are likely to be more effective in ensuring that digital finance contributes to inclusive economic participation rather than reproducing existing inequalities.

Keywords: *digital finance • financial inclusion • socio-economic disparities • digital financial services*

JEL codes: G21; O33; G51

Introduction

The ongoing trends in the financial sector have fundamentally changed the way financial services are delivered to clients. Especially the development of digital technologies and the expansion of mobile banking and digital payment systems have enabled the use of financial services via digital platforms. Hence, digital transformation has the potential to eliminate certain entry barriers for both clients and service providers. This can be achieved by increasing users' convenience and by including groups that were previously disadvantaged (Dudu et al., 2024). Digital financial services

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are seen as tools that can support financial inclusion by improving access and eliminating barriers (Kumari, 2026). On the other hand, increasing reliance on digital financial services is closely related to limited digital skills, digital infrastructure, and digital technology penetration. While these services may improve access to financial services and financial markets, their use may vary significantly according to socio-economic factors, such as age, education level, or place of residence (Petrikova & Kocisova, 2024). As a result, digitalisation in the financial sector may improve financial inclusion for the general population, but it can also increase existing disparities (Kowalewski & Pisany, 2021).

Considering the above-mentioned facts, this paper aims to examine the relationship between the use of digital financial services and financial inclusion. It analyses the socio-economic factors relevant to the adoption of basic and advanced digital financial services and investing. It examines whether their use reduces financial exclusion or perpetuates existing inequalities. The study focuses on two associated research questions. Firstly, it deals with socio-economic factors associated with the adoption of digital financial services. Secondly, it analyses whether the use of digital financial services reduces financial exclusion or reflects existing inequalities in access to financial services. The analysis distinguishes between basic digital financial services, such as mobile banking and digital payments, and advanced services that enable investments through digital technology.

The empirical analysis is based on micro-level Flash Eurobarometer survey data from more than 22,000 respondents covering all countries of the European Union. This survey is a collection of cross-country public opinion surveys conducted on behalf of the EU. To answer defined research questions, logistic and probit regression models are used. The obtained results suggest that the use of digital financial services varies considerably across socio-economic groups. While basic digital financial services are relatively widespread and associated with lower financial exclusion, advanced digital financial services are more concentrated among a smaller group of users, indicating that their adoption may be linked to existing socio-economic advantages. To incorporate our analysis into the broader academic debate, the following section reviews the relevant literature on digital financial services and financial inclusion.

Literature review

Digital financial services are financial services accessed and delivered through digital channels, including payments, savings, credit, investments, and insurance (Van Niekerk et al., 2021). These services are also supported by digital infrastructure and financial service markets (Rai et al., 2019). Due to the mentioned characteristics, they have the potential to be accessed by a population that is usually outside the traditional financial system (Owens, 2013). However, their diffusion remains significantly uneven. For example, within the EU, more than 30% of the population does not use them. It also means that exclusion rates are reaching 70% in some EU member states (Eurostat, 2022).

The examination of the reasons why certain groups remain excluded is based on three distinct yet complementary theoretical approaches. Firstly, the Technology Acceptance Model (TAM) framework explains digital adoption primarily through perceived usefulness and ease of use. It further reveals that excessive complexity and a lower level of trust tend to discourage individuals from using digital financial tools (Davis, 1989). Secondly, Digital Inequality Theory (DIT) extends the facts by identifying potential socio-economic factors. Based on this, it is evident that, for example, income, education, age, and gender may shape accessibility due to limited physical access to technology as well as differences in digital skills, autonomy, and social support (DiMaggio et al., 2004). Finally, Financial Inclusion Frameworks further develop the theory by identifying demand-side barriers, such as income and trust, and supply-side barriers, such as infrastructure problems (Demirgüç-Kunt et al., 2018). All of the mentioned theoretical concepts suggest that the adoption of digital technology should be examined in the context of individual socio-economic characteristics, structural factors, and the institutional environment, rather than solely on individual choice or technological availability.

Theoretical background helps us explain why digital financial exclusion is rather predictable and is driven by typical determinants. Moreover, it suggests that technologies often create greater exclusion for groups unable to keep pace with technological trends (Dostv et al., 2019; Mpofu, 2024). Typical barriers include infrastructural factors, skills, and gender disparities (Mpofu, 2024; Somogyvári, 2021). Moreover, trust issues, perceived security concerns, and complexity (Hussain et al., 2025; Jain et al., 2025). Most of these mechanisms directly correspond to TAM. Among socio-economic determinants, gender has received considerable attention, despite findings that are

currently not consistent. Most previous studies show that women are more likely to be financially excluded in the era of digitalisation (Alvarez-Franco et al., 2025; Biradar et al., 2025; Ngware, 2024).

Previous empirical evidence suggests a non-linear, inverted-U-shaped relationship between individuals' age and usage of digital financial services. While younger individuals benefit from familiarity with such technology, middle-aged individuals have greater digital competence and financial capacity. These factors appear to be even more important. Older individuals usually also have stronger motivation, which further explains the results achieved by Ba et al. (2025). They found that adoption was higher among people in the 25–50 cohort compared to those aged 15–24. Moreover, Ngware (2024) identifies a nonlinear effect of age, with a threshold at around age 52. Beyond this point, factors such as reduced skills, lower trust, and limited social support are likely to have a more significant effect (DiMaggio et al., 2004). Similarly, Petrikova and Kocisova (2024) found that adoption starts to decline around age 40. These findings led to the suggestion that policy interventions should be better tailored to each cohort. They need to consider each type of specific barrier.

Furthermore, previous studies also considered education as a significant determinant of digital adoption (Alvarez-Franco et al., 2025; Asante et al., 2025; Ba et al., 2025; Biradar et al., 2025; Chamboko, 2024; Negi et al., 2025). In line with TAM and Digital Inequality Theory, higher educational attainment is associated with lower perceived complexity and greater trust. It also builds cognitive capacity, which makes lower educational attainment one of the main disadvantages (Alvarez-Franco et al., 2025).

Employment status is also another factor potentially affecting adoption through income and professional exposure to digital tools. Employment tends to eliminate some of the barriers mentioned in both TAM and Digital Inequality Theory (Ba et al., 2025; Biradar et al., 2025). The effect is particularly significant for women, who also experience difficulties with their financial autonomy (Khusniati & Yusuf, 2025). Kumari (2026) confirms that employment is a crucial factor even in rural areas. Digital services may substitute for a limited formal financial infrastructure in such regions.

Moreover, Chamboko (2024) finds that self-employed individuals are frequently adopting digital financial services. Financial inclusion frameworks predict that urban areas, benefiting from better supply-side conditions, such as improved connectivity, infrastructure, and higher product availability. These regions usually exhibit higher adoption rates, as confirmed by Ayemi (2025) and Chamboko (2024). However, this evidence is largely based on data from developing countries and regions, including South Asia, Latin America, Indonesia, Nigeria, and Uganda, limiting applicability to the EU context and motivating RQ1.

RQ1: What socio-economic factors determine the adoption of basic and advanced digital financial services in countries of the European Union?

Given the growing importance of digital financial services, it is crucial to examine their effects on financial inclusion outcomes. Empirical evidence mostly supports a positive relationship. Digital financial services are identified as one of the strongest predictors of financial inclusion (Kumari, 2026) because they expand access to banking, credit, and financial products in underserved areas (Gao, 2025; Ocharive & Iworiso, 2024; Tiony et al., 2023). However, Digital Inequality Theory predicts that these benefits will be unequally distributed with bias towards individuals with already better skills, income, and social support. This prediction finds empirical support. Al-Masaeid et al. (2026) show that digital illiteracy and infrastructure deficiency limit the reach of digital financial services among the most excluded groups, while Bajpai (2024) argues that FinTech advancements can harm those unable to keep pace with technological change. Agwu (2020), Mpofu (2024) and Somogyvári (2021) go further, arguing that digital financial services can actively worsen exclusion where the barriers remain. The gendered dimension of this risk is particularly important. Jiang et al. (2022) and Mpofu (2024) found negative effects on women. Given this mixed evidence, the overall effect of digital financial services on financial inclusion in the European Union context remains debatable, as reflected in our second research question (RQ2).

RQ2: Do digital financial services mitigate or reinforce financial inclusion in the context of the European Union?

By addressing both research questions, this study moves beyond identifying who adopts digital financial services to examine the consequences of adoption patterns for financial inclusion outcomes, providing a theoretically grounded and empirically focused contribution within the underexplored European Union context.

Research methodology

To address the mentioned research questions, the empirical analysis relies on micro-level survey data from Flash Eurobarometer 509, which provides information about the use of financial services and socio-economic characteristics for each respondent. The dataset covers respondents from all EU countries. A non-probability quota sampling technique was used to select a sample. After excluding observations with missing values, the final sample includes 22,653 observations. The sample size provides sufficient statistical power for the logistic and probit regression models employed in this study. Based on commonly applied guidelines for logistic regression, a minimum of 10 events per predictor variable is recommended (Peduzzi et al., 1996). Given the number of predictors included in the models and the prevalence of the outcome variables, this criterion is satisfied across all estimated models, supporting the reliability of the obtained results.

Use of digital financial services is captured by two composite indices: basic and advanced. The first index reflects the use of a mobile banking app or website to authenticate identity and check balance, and the use of a banking or payment app/ website to pay in shops or online. The index of advanced digital financial services includes the use of a mobile app to invest in financial markets and crypto-assets. Both indices are constructed from the recorded frequency of use of individual digital financial services, which were transformed into a numerical scale (Table 1).

The upper part of Table 1 presents the recoding of the original frequency categories into a numerical scale. Daily use categories were merged into a single value of 3, reflecting qualitatively similar patterns of regular engagement. Weekly and monthly use categories were assigned values of 2 and 1, respectively, while non-use was coded as 0. To verify that the findings are not sensitive to this recoding procedure, an alternative specification retaining the original six-point ordinal scale was also constructed. The lower part of Table 1 presents the validation of both composite indices. Cronbach's alpha exceeded the recommended threshold of 0.70 (Nunnally, 1978) for both indices, confirming good reliability and supporting the validity of aggregating individual service usage into composite indices. Recoded values were summed with equal weights, justified by the absence of a theoretical basis for differential weighting and further supported by the weak factor structure indicated by the KMO test, which does not support the use of factor analysis. In addition, financial inclusion is measured using a composite index reflecting the use of financial products. The index is constructed based on information about current and savings accounts, payment and private pension or retirement products, mortgage or other loans, investment products, and cryptocurrencies. Each product is coded as a binary variable indicating whether it is used. These variables are summed up to create an overall financial inclusion variable. To capture financial exclusion, binary indicators are constructed based on the level of financial inclusion; specifically, individuals with absolute exclusion ($FI=0$) or with low use ($FI \leq 1$). This methodology is also applied to digital financial exclusion, enabling the distinction between different levels of digital financial inclusion. Created variables about digital financial exclusion were used as the dependent variable in logistic and probit regression models. Logistic regression estimates the log-odds of exclusion as a function of socio-economic characteristics, while the probit specification serves as a robustness check by assuming a normal rather than logistic distribution of the error term. Both specifications are reported to confirm the stability of the findings. (Table 2).

Table 3 presents the socio-economic characteristics of the sample. The largest age group consists of respondents aged 65 and older, while the gender distribution is relatively balanced. In terms of educational attainment, the

Table 1. Recoding of frequency of use and index validation. (Source: Created by the author)

Original response category	Recoded value	Alternative recoded value	
Several times a day	3	5	
At least once a day	3	4	
At least once a week	2	3	
At least once a month	1	2	
Less than once a month	1	1	
Never (I don't have such an app)	0	0	
Validation of indices			
	Range (Alternative range)	Cronbach's α	Inter-item correlation (r)
Basic digital financial services	0-6 (0-10)	0.75	0.60
Advanced digital financial services	0-6 (0-10)	0.73	0.59

Table 2. Definition of socio-economic characteristics. (Source: Created by the author)

Variable	Description
Age	Age of respondents grouped into categories: 15-24, 25-34, 35-44, 45-54, 55-64 and 65 years and older
Gender	Gender of respondent coded as 1 if female and 0 if male
Education	Age at which respondent completed full-time education: up to 15 years, 16-19 years, 20 years and older, still studying or never attended full-time education
Labour status	Current labour status of respondent: employee, self-employed, without professional activity or manual worker
Locality	Area of residence: large town/city, small or medium-sized town or rural area/village
Physical access	Ease of access to cash withdrawal via ATM or bank branch, coded 1 if very easy or rather easy, and 0 if rather difficult or very difficult

Table 3. Socio-economic characteristics of the sample. (Source: Created by the author)

Variable	Distribution
Age	15-24 (10.9 %), 25-34 (15.0 %), 35-44 (17.4 %), 45-54 (18.4 %), 55-64 (16.9 %), 65+ (21.4 %)
Gender	Male (49.0 %), Female (51.0 %)
Education	No education (1.8 %), Low (2.7 %), Medium (32.4 %), High (54.7 %), Still studying (8.5 %)
Labour status	Employee (50.5 %), Manual worker (5.7 %), Self-employed (11.1 %), Without professional activity (32.6 %)
Area	Large city (34.9 %), Small or medium town (39.8 %), Rural area, or village (25.4 %)

majority hold higher education qualifications. Employees represent the largest share by labour market status, followed by those without professional activity. Regarding place of residence, respondents are relatively evenly distributed across large cities, small or medium-sized towns, and rural areas.

Logistic regression is employed as it is suitable for modelling binary outcome variables and enables the estimation of the probability of digital financial exclusion. The results are interpreted using odds ratios and complemented by the estimation of average marginal effects to provide a more intuitive interpretation. To ensure the robustness of the findings, probit models are also estimated as an alternative specification.

The second part of the research examines the relationship between digital financial services and financial inclusion. For this purpose, financial exclusion is modelled as a binary variable. The main independent variables are the indices of basic and advanced digital financial services. Alongside these variables, models also include socio-economic determinants to assess whether the use of digital financial services reduces financial exclusion or reflects existing inequalities. The relationship is estimated using logistic regression models. To further explore potential heterogeneity in the effects of digital financial services, interaction terms are introduced.

Research results

Looking at the use of digital financial services in this sample, a significant difference between basic and advanced services is observed in Table 4. The basic services index averages 3.81, indicating relatively widespread adoption, with only 6.6% of respondents showing absolute non-use and 10.3% classified as low users.

In contrast, advanced digital financial services show markedly lower adoption, with an average index value of 0.81. Absolute exclusion affects 66.2% of respondents, rising to 78.9% under the broader definition. While basic services have become a common part of everyday life, advanced products remain significantly unevenly distributed, motivating the analysis of determinants of digital financial exclusion that follows.

The results indicate significant socio-economic stratification in basic digital financial service use, with age emerging as the strongest determinant. Compared to the reference group aged 35–44, younger individuals show lower likelihood of exclusion, while those aged 45 and older are progressively more likely to be excluded, with respondents aged 55 and older showing odds of exclusion twice those of the reference group. Consistent with Digital Inequality Theory (DiMaggio et al., 2004), this pattern reflects not merely generational preference, but a structural barrier rooted in differential accumulation of digital capital. Older individuals may possess formal device access yet lack the confidence, skills, and social support necessary for meaningful engagement. This implies that effective interventions should target digital financial literacy and trust rather than device access alone.

Table 4. Descriptive statistics and prevalence of digital financial exclusion. (Source: Created by the author)

	Mean (SD)	Absolute exclusion (0) %	Low use (≤ 1) %
Basic digital financial services (0-6)	3.81 (1.73)	6.6	10.3
Advanced digital financial services (0-6)	0.81 (1.44)	66.2	78.9

Labour market status represents another significant determinant. Compared to employees, manual workers show a higher likelihood of exclusion, while respondents without professional activity face odds of exclusion more than twice those of the reference group. This particularly strong effect points to the compounding nature of socio-economic disadvantage. Labour market inactivity simultaneously reduces income, limits professional exposure to digital tools, and restricts access to employer-provided financial products, creating a self-reinforcing cycle where those most in need of accessible financial services are least likely to adopt them. This challenges the narrative of digital finance as a universally accessible inclusion tool and suggests it may reproduce rather than disrupt existing labour market stratification.

Stratification is also evident in educational attainment. While the difference between lower and secondary education is not statistically significant, higher education is associated with a lower likelihood of exclusion, while those without formal education face higher odds. Consistent with both TAM and Digital Inequality Theory, education reduces perceived complexity, enhances trust, and builds the cognitive resources necessary for effective engagement. Place of residence represents the last statistically significant determinant, with rural residents showing a slightly higher likelihood of exclusion than large city residents, while the result for medium-sized towns is not statistically significant. Gender and physical access to services do not play a significant role at the basic service level. The consistency of results across regression models confirms the robustness of these findings. Figure 1 presents the average marginal effects of statistically significant determinants on the probability of basic digital financial exclusion.

Figure 2 confirms age and labour market status as the key determinants of basic digital financial exclusion. The strongest effect is observed among respondents without professional activity, with exclusion probability exceeding 5 percentage points above the reference group, while self-employed persons show a decreased likelihood. A similarly strong age gradient is evident, with respondents aged 55 and older showing approximately 5 percentage points higher probability of exclusion than the reference group. For remaining significant determinants, the observed associations are weaker in magnitude. The consistency of results across logit and probit specifications in Table 5 and the alternative outcome definition ($\text{DFS} \leq 1$) confirms the robustness of these findings, demonstrating that socio-economic inequalities in digital financial exclusion are not only statistically significant but also economically meaningful.

The previous models focused on basic digital financial services, mobile banking, and digital payments. However, adoption of more sophisticated services such as investment and crypto applications typically requires higher levels of digital skills, financial literacy, and risk tolerance, and may therefore reflect deeper socio-economic stratification. Table 6 presents the regression results for advanced digital financial exclusion.

The results for advanced digital financial exclusion point to even more pronounced socio-economic stratification than observed for basic services. Age remains the key determinant but with a steeper gradient. Individuals aged 45 and older are more than twice as likely to be excluded, with the gradient strengthening substantially for those aged 55 and above. This steeper gradient reflects the greater complexity of advanced tools, which amplifies second-level digital inequalities among older cohorts (DiMaggio et al., 2004).

Gender emerges as an additional key determinant at this level. The absence of a gender effect for basic services contrasted with a pronounced gap for advanced services suggests that the divide is driven not by access barriers but by differences in risk tolerance, financial literacy, and exposure to investment products, reflecting broader structural inequalities in income and wealth accumulation (Jiang et al., 2022). This implies that gender-targeted interventions should focus specifically on advanced digital financial tools rather than basic access.

Labour market status remains strong, with inactive respondents facing odds nearly twice as those of employees, while the self-employed show reduced likelihood of exclusion, reflecting greater exposure to investment products. Higher education and urban residence continue to be associated with lower exclusion, with the rural-urban divide persisting consistently across both service levels. The consistency of results across logit and probit specifications

confirms robustness, and the stronger magnitudes at the advanced level indicate that advanced digital financial participation reflects deeper layers of socio-economic inequality.

Figure 2 confirms the importance of these determinants. The age gradient is notably steeper than for basic services. Individuals aged 45–54 show approximately 10 percentage points higher probability of exclusion than the reference group, rising to almost 15 percentage points for those aged 55 and older, consistent with the amplification of second-level digital inequalities by greater service complexity. A similarly strong effect is observed for labour

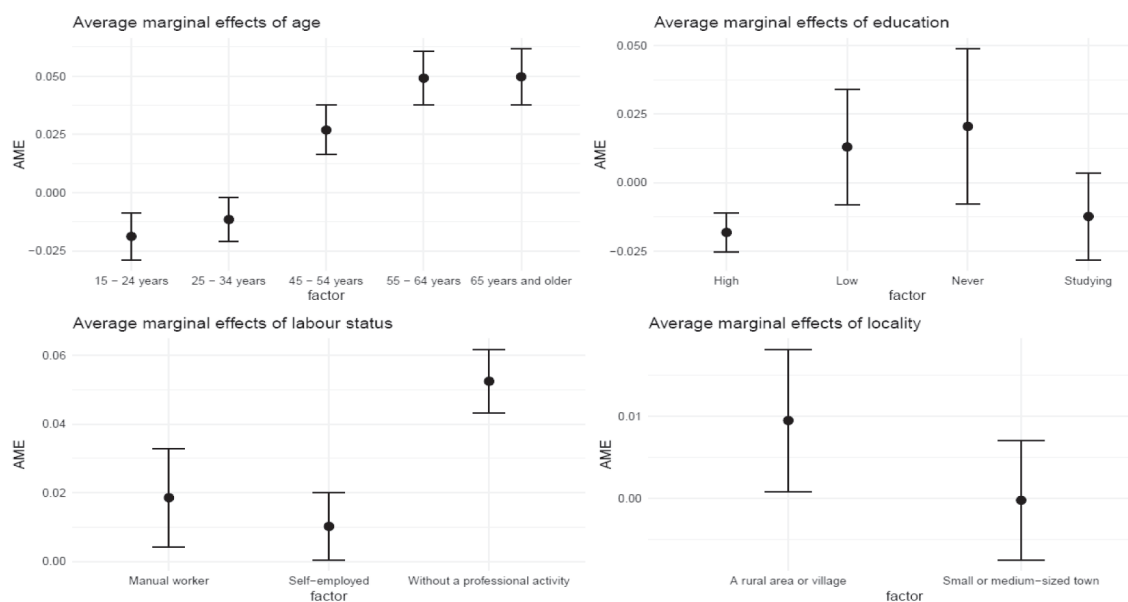


Figure 1. Average marginal effects of determinants on basic digital financial exclusion (Source: Created by the author)

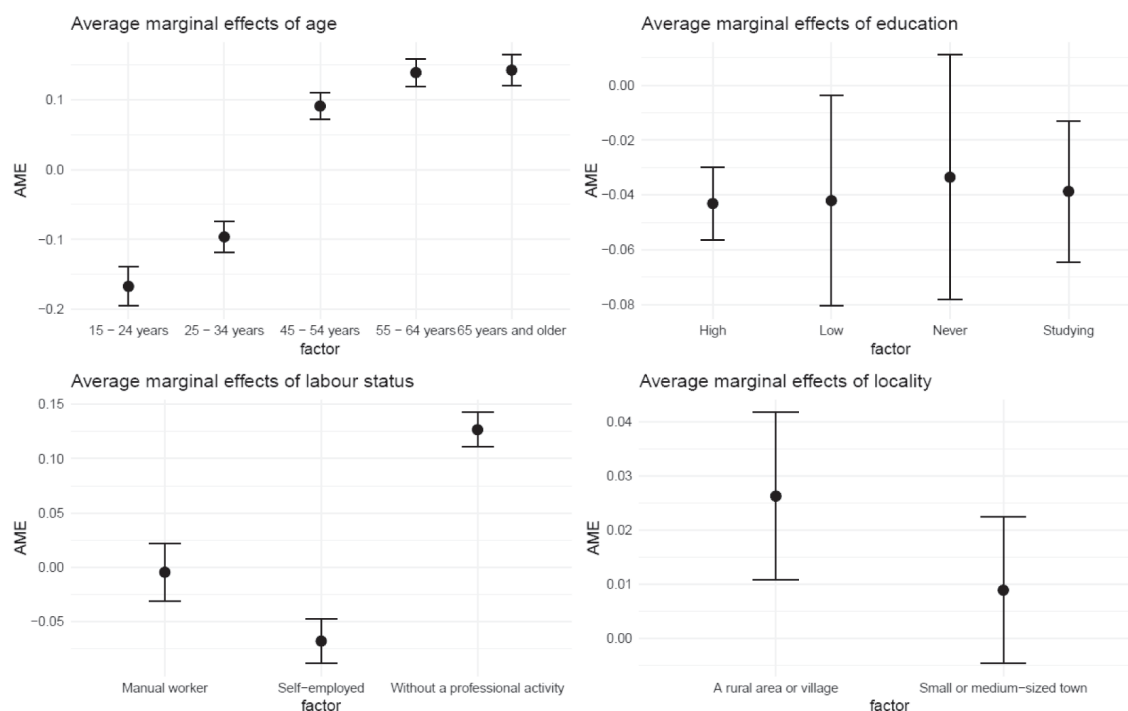


Figure 2. Average marginal effects of determinants on advanced digital financial exclusion. (Source: Created by the author)

Table 5. Results of regression models analysing determinants of basic digital financial exclusion. (Source: Created by the author)

Variable	Basic digital financial exclusion		
	Logit (0)	Logit (0-1)	Probit (0)
15-24 years	0.572** (0.134)	0.624*** (0.126)	-0.2633 (0.0005**)
25-34 years	0.704* (0.144)	0.705*** (0.110)	-0.1462 (0.0176*)
45-54 years	1.693*** (0.111)	1.610 (0.087**)	0.2463 (1.01e ⁻⁰⁶ ***)
55 – 64 years	2.302*** (0.109)	2.133*** (0.086)	0.3991 (6.43e ⁻¹⁶ ***)
65 and more	2.299*** (0.116)	2.124*** (0.091)	0.4027 (3.95e ⁻¹⁵ ***)
Female	1.107 (0.056)	1.133** (0.046)	0.04311 (0.1117)
No education	1.297 (0.177)	1.271 (0.150)	0.1394 (0.1249)
Low education	1.184 (0.136)	1.106 (0.117)	0.0912 (0.2035)
High education	0.732*** (0.059)	0.739*** (0.049)	0.1509 (3.14e ⁻⁰⁷ ***)
Still studying	0.838 (0.140)	0.839 (0.111)	-0.0987 (0.1468)
Manual worker	1.472** (0.133)	1.344** (0.109)	0.1785 (0.0046**)
Self-employed	1.257* (0.105)	1.237* (0.083)	0.1042 (0.3210*)
Without a professional activity	2.321*** (0.080)	2.194*** (0.064)	0.4187 (2e ⁻¹⁶ ***)
Small or medium-sized town	1.002 (0.065)	0.980 (0.053)	-0.0021 (0.9472)
Rural area or village	1.160* (0.073)	1.068 (0.060)	0.0768 (0.0313*)
Physical access	1.070 (0.082)	1.023 (0.067)	0.0293 (0.4635)
Statistics			
Observations	22653	22653	22653
Log-likelihood	-5125.799	-5121.514	-5121.514
AIC	10286	14097	10277

market inactivity, reaching almost 15 percentage points, while the self-employed show decreased probability. Differences by education and place of residence are evident but weaker in magnitude. The consistency of results across logit and probit specifications in Table 6 and the alternative outcome definition ($DFS \leq 1$) confirms the robustness of these findings.

Across all models, basic digital financial services are associated with significantly lower odds of financial exclusion, while advanced services show slightly higher odds. Basic services thus function as broad inclusion tools, while advanced services reflect more selective participation concentrated among socio-economically advantaged groups. This asymmetry suggests that the inclusion potential of digital finance is real but bounded, operating primarily at the transactional level while leaving deeper financial inequalities largely undisturbed. The robustness of these findings is confirmed by the alternative index specification, with both DFS coefficients remaining directionally consistent and the lower AIC of the original model supporting it as the preferred specification.

Turning to heterogeneity, moderator effects confirm that individuals with low education and those without professional activity face higher odds of exclusion. However, interaction terms are generally small and statistically weak, suggesting that the inclusion effect of basic services operates relatively uniformly across population groups. Similarly, advanced services show stable associations across socio-economic categories, implying that advanced digital finance reflects and reproduces rather than reduces existing inequalities.

Table 6. Results of regression models analysing determinants of advanced digital financial exclusion. (Source: Created by the author)

Variable	Advanced digital financial exclusion		
	Logit (0)	Logit (0-1)	Probit (0)
15-24 years	0.481*** (0.065)	0.456*** (0.067)	-0.4482 (2e-16***)
25-34 years	0.656*** (0.048)	0.578*** (0.052)	-0.2606 (2e-16***)
45-54 years	1.556*** (0.048)	1.623*** (0.056)	0.2606 (2e-16***)
55 – 64 years	2.035*** (0.052)	2.447*** (0.064)	0.4224 (2e-16***)
65 and more	2.105*** (0.058)	3.261*** (0.076)	0.4345 (2e-16***)
Female	2.162*** (0.031)	2.493*** (0.036)	0.44586 (2e-16***)
No education	0.856 (0.117)	0.800 (0.134)	-0.1035 (0.13356)
Low education	0.803* (0.096)	0.657 (0.111)	-0.1292 (0.0284*)
High education	0.804*** (0.035)	0.909* (0.041)	-0.1323 (1.87e-10***)
Still studying	0.816** (0.066)	0.796** (0.073)	-0.1191 (0.0027**)
Manual worker	0.979 (0.062)	1.078 (0.069)	-0.0129 (0.7377)
Self-employed	0.733*** (0.046)	0.679*** (0.051)	-0.1894 (4.03e-14***)
Without a professional activity	1.960*** (0.044)	2.087*** (0.055)	0.3935 (2e-16***)
Small or medium-sized town	1.049 (0.035)	1.087* (0.040)	0.0270 (0.1950)
Rural area or village	1.147*** (0.040)	1.187*** (0.047)	0.0803 (0.0009***)
Physical access	0.966 (0.045)	0.996 (0.052)	-0.0184 (0.4905)
Statistics			
Observations	22653	22653	22653
Log-likelihood	-13056.77	-10182.65	-13065.27
AIC	26148	20399	26165

Table 7. Results of regression models analysing determinants of advanced digital financial exclusion. (Source: Created by the author)

	Moderators						
	Raw association	Baseline model	Alternative index	Above 54 years old	No/Low education	Without professional activity	Rural or village
DFS_basic	0.79* (0.011)	0.78* (0.012)	0.85* (0.009)	0.81*** (0.015)	0.78*** (0.012)	0.80*** (0.015)	0.77*** (0.014)
DFS_advanced	1.08* (0.014)	1.04* (0.015)	1.02* (0.010)	1.06*** (0.015)	1.04* (0.015)	1.03* (0.155)	1.04* (0.015)
Moderator effect	No	No	No	0.82* (0.085)	1.48* (0.186)	1.79*** (0.090)	0.82* (0.097)
DFS_basic x Moderator	No	No	No	0.94** (0.023)	1.03 (0.051)	1.01* (0.023)	1.05* (0.025)
DFS_advanced x Moderator	No	No	No	1.07 (0.039)	1.07 (0.061)	1.01 (0.036)	1.08** (0.031)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22653	22653	22653	22653	22653	22653	22653
AIC	18087	17352	17392	17468	17353	17347	17350

These findings demonstrate that while digital financial services are associated with financial inclusion, their effects differ substantially by service complexity. Basic services support broad inclusion while advanced services leave underlying socio-economic disparities largely intact.

Conclusions

This study provides empirical evidence of the role of digital financial services in financial inclusion within the European Union. The results confirm that digital financial exclusion remains unevenly distributed across population groups and differs substantially between basic and advanced services. Exclusion is more prevalent among older individuals, the economically inactive, rural residents, and those with lower educational attainment. Gender differences were statistically significant only for advanced services, where women appeared more disadvantaged.

A key contribution of this study is the distinction between basic and advanced digital financial services and their theoretical interpretation. Basic services support broad financial inclusion, while advanced services remain concentrated among socio-economically advantaged groups, reflecting and reproducing existing inequalities. This asymmetry validates the integrated theoretical framework proposed in this study: TAM explains individual-level barriers such as perceived complexity and low trust, Digital Inequality Theory accounts for the structural reproduction of exclusion through second-level inequalities amplified by service complexity, and financial inclusion frameworks confirm that both demand-side barriers, like education, employment, and age, as well as supply-side conditions, such as rural infrastructure, jointly shape participation in digital finance.

From a methodological perspective, the construction of separate validated composite indices enables a more nuanced examination of digital financial participation than binary measures typically employed in existing literature. The use of data for EU countries provides broader geographical scope than most existing studies focused on developing regions. Robustness checks across alternative specifications strengthen confidence in the reported associations.

Overall, digitalisation alone is insufficient to eliminate financial exclusion. Reducing persistent disparities requires targeted support for digital and financial literacy and measures aimed at vulnerable groups. This study has several limitations. The cross-sectional design precludes causal inference, and reverse causality cannot be excluded. Unobserved individual characteristics may introduce omitted variable bias, and the dataset does not capture psychological factors such as trust or digital self-efficacy. Future research employing panel data, quasi-experimental designs, or qualitative approaches would be better positioned to establish causal mechanisms and explore barriers among vulnerable groups.

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Declaration of generative AI in scientific writing

During the preparation of this work, the authors used the Grammarly AI tool to check grammatical correctness, proofread, and polish the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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