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Digital Financial Inclusion and Financial Vulnerability: An Exploratory Analysis of Spanish Households

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Abstract

Public authorities have increasingly focused on digital financial inclusion (DFI) owing to its potential to enhance overall financial inclusion (FI) and, ultimately, to mitigate households' financial vulnerability (FV). Although the existing literature generally reports a negative relationship between DFI and FV, most studies focus on economically less developed countries and apply heterogeneous measurement approaches. This study adopts a quantitative methodology to assess DFI as a potential determinant of FV in a developed economy—Spain—using both objective and subjective indicators of FV. DFI is proxied by the diversity of payment and transfer methods conducted via Internet and mobile devices. Empirical findings confirm a negative association between DFI and FV, indicating that higher levels of digital engagement are associated with lower FV. However, results also reveal a potential adverse effect on savings behaviour, possibly linked to the reduced "pain of paying" commonly associated with online transactions. These insights suggest that policies promoting DFI should be complemented by initiatives to enhance financial literacy, strengthen consumer protection laws, and reintroduce the "feel of cashback" within online payment platforms. By providing evidence from a developed country, this paper contributes to the limited literature by also examining subjective measures of FV variables and offline FI.

Keywords: financial inclusion; digitalization; financial fragility; household finances

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1. Introduction

Since the collapse of the dot-com bubble in the early 21st century, the financial sector has progressively integrated digital technologies into its operations (Ozili, 2023; Wang & Mao, 2023). Over time, the availability and use of financial products and services—such as payment systems, savings instruments, and credit facilities—have expanded significantly through digital channels, including the Internet and mobile platforms. In Spain, online banking usage reached 71.45% of the population in 2023, surpassing the European Union average of 63.87% (FUNCAS, 2024). The OECD (2018) conceptualizes this phenomenon as digital financial inclusion (DFI), underscoring that access and usage must remain affordable, secure, and responsive to users' needs.

Building on this expansion, public authorities have shown growing interest in the potential of digitalisation to enhance households' financial inclusion (FI). By lowering transaction costs compared with traditional channels, digital finance may contribute to overall economic well-being (Al Khub et al., 2024; J. Liu et al., 2024). This development has also sparked academic interest in assessing whether DFI effectively strengthens households' financial resilience. Some studies highlight that DFI can support savings behaviour (Loaba, 2022) and improve financial decision-making (Mishra et al., 2024), particularly in unforeseen circumstances (Wang & Mao, 2023; J. Liu et al., 2024; Verma & Chatterjee, 2025). However, other studies warn of the risks associated with immediate access to digital products such as instant credit and online payments. These products may lead to excessive indebtedness and, consequently, increase financial vulnerability (FV), particularly among individuals with impulsive behaviours or limited financial literacy (Seldal & Nyhus, 2022; Qiu et al., 2025).

Against this backdrop, a growing number of studies have empirically examined the relationship between DFI and FV. However, much of this literature focuses on developing countries and tends to overlook the subjective dimension of FV, as well as the interaction between offline FI and DFI. This paper seeks to address these gaps by analysing the relationship between DFI and FV among Spanish households. In particular, it explores whether the use of Internet and mobile-based payment methods is associated with reduced financial resilience. To address this objective, the analysis draws on a sample of 1000 households residing in Spain, extracted from the 2021 *Global Findex Database* (GFD).

This research contributes to the literature on DFI and FV by extending the limited empirical evidence on this relationship available for economically developed countries, specifically in the Spanish context. Moreover, it adopts a comprehensive approach to both phenomena by incorporating indicators of both objective and subjective FV, together with measures of DFI and offline FI. This integrated approach offers new insights for future studies drawing on data from GFD.

The remainder of this paper is structured into four sections. Section 2 reviews the limited body of literature that has examined this topic. Section 3 outlines the methodological approach, describing the data source, the variables employed, and the econometric models applied. Section 4 presents the empirical results, beginning with a descriptive analysis of the key variables and followed by a discussion of the findings from the multivariate analysis. Finally, Section 5 summarizes the main conclusions, discusses the theoretical and practical implications, identifies the study's limitations and proposes avenues for future research.

2. Literature Review

DFI is a relatively recent phenomenon, and all studies identified that examine its relationship with household FV (see Table 1) have been published since 2020. This body of research is markedly heterogeneous, largely due to substantial differences in how FV is measured and conceptualised (Fernández-López et al., 2024).

Most previous studies consider only objective measures of households' financial situation. More specifically, while some rely on indicators related to saving capacity—particularly the ability to sustain savings to cover unexpected expenses (Loaba, 2022; Verma & Chatterjee, 2025)—others adopt broader approaches. These studies incorporate measures such as the level of debt relative to income (Wang & Mao, 2023; J. Liu et al., 2024), financial margins (Qiu et al., 2025), or the risk of falling back into poverty (Hu et al., 2024; Xu et al., 2024).

Research based exclusively on objective measures of FV tend to focus predominantly on developing and emerging economies, particularly in Africa—such as Nigeria (Loaba, 2022)—and Asia, including Indonesia (Saputro et al., 2024) and, most notably, China (L. Liu & Guo, 2023; Hu et al., 2024; J. Liu et al., 2024; Qiu et al., 2025; Xu & Zhang, 2025). China stands out as the most extensively analysed country, perhaps due to the availability of its own DFI indicators. Consequently, studies on China typically employ an index developed by Peking University, which assesses DFI across three dimensions (i.e., coverage, depth of use and level of digital support). These studies generally measure DFI in aggregate terms, assuming that all households within a given geographical area (e.g., districts, cities, regions) experience the same level of DFI.

Table 1. Summary of literature relating DFI and FV.

Reference [Country (Year; Sample)]	Dependent FV Variables (Type of Variable—*Type of Measure*) [Detail]: (*Statistical Model*)	*Level of DFI/FI*: Main Independent Variable (Type of Variable—*Type of Measure*) [Detail]
	Positive relationship	
Loaba (2022) [Seven West African countries (2017; 6074 individuals)] *	Did you save any money during the past year? (0–1: yes—*Obj.*) [in a formal financial institution, informal financial institution, or both]: (*SEM, probit and multinomial logit*)	*Digital individual/household level*: • Mobile banking (0–1: yes—*use*) • Mobile/electronic money (0–1: yes—*use*)
Seldal and Nyhus (2022) [Norway (2018; 2202 adults)]	• Difficulty paying monthly invoices (0–1: some difficulty—*Subj.*) • Use of consumer credit for non-durable goods (0–1: yes—*Obj.*) • Inability to cover three months of expenses with savings (0–1: yes—*Obj.*) (*Logit*)	*Digital individual/household level*: Digital payment technologies (0–1: yes—*use*) [mobile payments (e.g., *Vipps*, *MobilePay*), online payments (e.g., *PayPal*, *Klarna*)]
Hu et al. (2024) [China (2013, 2015, 2017, and 2019; 3254 households)] **	Absence of poverty (continuous variable—*Obj.*) [income per person and day]: (*OLS*)	*Digital individual/household level*: Availability of a formal loan, a bank deposit, ownership of commercial insurance, and possession of a credit card (continuous variable—*access*) *Digital aggregated level*: DFI index of the province where the household is located (continuous variable—*mixed*)
Qiu et al. (2025) [China (2017–2019; 35,603 households)] ***	• Financial margin (0–1: negative value—*Obj.*) [income less ordinary and financial expenses] • Debt-to-income ratio (0–1: >30%—*Obj.*) (*Probit*)	*Digital individual/household level*: • Online shopping (0–1: yes—*use*) • Online shopping (continuous variable—*use*) [logarithm of per capita spending on online purchases] • Digital payments (0–1: yes—*use*)
Verma and Chatterjee (2025) [13 emerging countries in America, Africa, and Asia (2014 and 2021; 33,933 individuals)] *	Financial resilience (0–1: yes—*Obj.*) [pay an amount (equivalent to 1/20 of the country's gross national income (per capita) in the next 30 days due to an emergency)]: (*Probit*)	*Digital individual/household level*: • Digital loans (0–1: yes—*use*) [through credit cards] • Make digital payments (0–1: yes—*use*) [through cards or mobile accounts] • Receive digital payments (0–1: yes—*use*) *Offline level*: • Use an offline bank account (0–1: yes—*use*) • Have an offline bank account (0–1: yes—*access*)
	Negative relationship	
L. Liu and Guo (2023) [China (2015–2019; 29,625 households)] **	FV index on relative household poverty (continuous variable—*Obj.*) [sum of economic, health, and quality of life variables]: (*Multiple regression with fixed effects*)	*Digital aggregated level*: DFI index of the city where the household is located (continuous variable—*mixed*) [overview of coverage, depth of use, and level of digital support]
Wang and Mao (2023) [China (2016 and 2018; 11,967 individuals)]	FV index (0 to 2—*Obj.*) [sum of situations: if savings do not exceed three months of daily expenses (0–1: yes) and annual debt-to-income ratio exceeds 30% (0–1: yes)]: (*Ordered probit*)	*Digital aggregated level*: DFI index of the district where the household is located (continuous variable—*mixed*) [log transformation]
J. Liu et al. (2024) [China (2019; 27,080 households)] **	FV index (0 to 3—*Obj.*) [sum of situations: if expenses exceed annual income (0–1: yes), savings do not exceed three months of daily expenses (0–1: yes), and annual debt-to-income ratio exceeds 30% (0–1: yes)]: (*ordered probit*)	*Digital aggregated level*: DFI index of the province where the household is located (continuous variable—*mixed*) [log transformation]
Xu et al. (2024) [China (2017; 3156 individuals)] **	Risk of returning to poverty (0–1: yes—*Obj.*) [substantial loss of health, education, well-being, and confidence]: (*Probit*)	*Digital aggregated level*: Household DFI index: (continuous variable—*mixed*) [degree of digitization (use of electronic payments and accounts); usability (purchase of commercial or social insurance, bank loans, and credit cards); coverage (distance from home to the nearest bank)]
Xu and Zhang (2025) [China (2017–2019; 12,801 rural households)] **	Financial margin (0–1: <0—*Obj.*) [income + liquid assets − daily expenses – debts − unexpected expenses]: (*Probit*)	*Digital individual/household level*: Digital payment in 2017 (0–1: yes—*use*) [*Alipay*, *WeChat Pay*, mobile banking, etc., via devices like smartphones and tablets]
	Non-significant relationship	
Saputro et al. (2024) [Indonesia (2023; 95 management undergraduates)] ***	FV index (ordinal variable) [difficulty meeting unexpected expenses and covering basic costs, and use of consumer credit]: (*Regressions*)	*Digital individual/household level*: Digital payments (ordinal variable—*use*)

Notes: *, **, and *** indicate that the study sample is drawn from the *Global Findex Database*, the *China Household Finance Survey* and the authors' own survey, respectively. *Obj.* and *Subj.* stand for objective and subjective FV measures, respectively. *SEM* and *OLS* stand for *Structural Equation Modelling* and *Ordinary Least Squares*, respectively. The label *0–1* denotes a dummy variable, whereas # *to* # refers to ordinal variables with known extreme values. Certain data have been omitted due to insufficient detail in some of the reviewed manuscripts.

Studies employing these aggregate measures consistently find a negative relationship between DFI and FV. In this vein, living in a region with greater availability of digital financial services is typically associated with lower household deficits (J. Liu et al., 2024) or a reduced risk of poverty (L. Liu & Guo, 2023; Xu et al., 2024). The underlying argument is that DFI facilitates access to, and use of, financial products and services which, if obtained through traditional channels, would entail higher transaction costs (Figure 1). These arguments are consistent with the theoretical framework of financial capability (Sherraden, 2013), which emphasizes that FI—understood as the opportunity to act—requires financial products and services that are accessible and usable in order to strengthen financial resilience, especially among the most vulnerable households. To this end, financial services must be accessible, affordable, financially attractive, easy to use, flexible, secure and reliable (Sherraden, 2013).

Many of these features can be delivered more effectively through digital financial channels. Individuals can now use their smartphones to invest in stocks or mutual funds, thereby saving the time and potential costs associated with visiting a financial institution. Digital platforms are characterised by high levels of accessibility, a wide range of services and intuitive, user-friendly interfaces (Al Khub et al., 2024). These attributes strengthen the argument that DFI can mitigate FV to a greater extent than traditional FI.

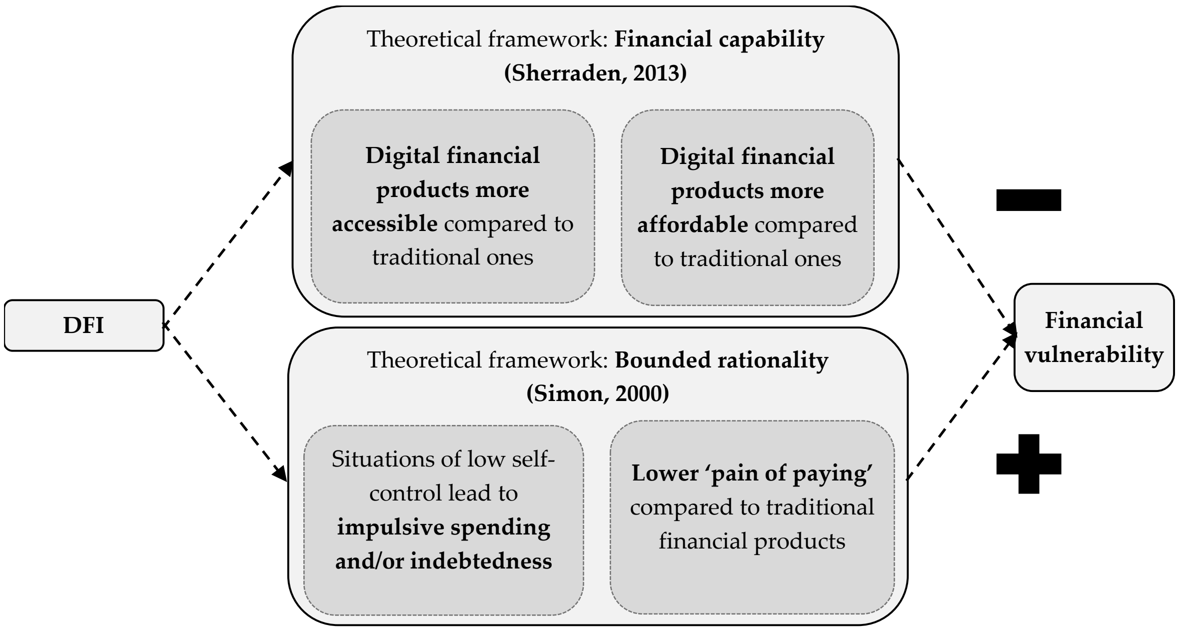

Figure 1. Theoretical frameworks linking DFI and FV. Notes: Simon (2000) and Sherraden (2013).

In contrast to the arguments outlined above, another group of authors contends that aggregate indicators place excessive emphasis on the usage dimension of DFI, noting that mere access does not necessarily translate into effective FI. Consequently, aggregate measures of DFI are increasingly being replaced or complemented by indicators constructed at the individual or household level (e.g., Loaba, 2022; Hu et al., 2024; Qiu et al., 2025). These DFI indicators typically capture the use of digital payment methods, such as mobile phones, Internet-based platforms, digital accounts or other electronic systems. In studies employing these variables—which also predominantly examine less economically developed countries and rely on objective measures of FV—positive associations between DFI and FV are most frequently observed.

Specifically, DFI—when measured through the ability to make digital payments—may promote excessive (Xu & Zhang, 2025) or irrational (Qiu et al., 2025) household consumption. This behaviour can lead to over-indebtedness and non-payment of credit card balances, ultimately undermining households' financial resilience. From the perspective of behavioural economics, which integrates psychological factors into the analysis of decision-making, individuals are subject to bounded rationality (Simon, 2000). In other words, decisions are often suboptimal due to constraints on time, resources, or self-control. This latter is particularly relevant in digital environments, characterized by immediacy and ease of access, where impulsive behaviour becomes more likely. For example, mobile shopping encourages impulsiveness by eliminating the need to visit physical stores and enabling instant payment through digital channels. Moreover, online shopping platforms create virtual environments designed to enhance the user experience, thereby encouraging impulsive consumption and increased spending (Qiu et al., 2025).

Furthermore, although payments are generally associated with a negative feeling—often referred to as the "pain of paying"—this perception of loss is more pronounced when using transparent payment methods such as cash (Seldal & Nyhus, 2022). In these cases, individuals are more aware of the money they are spending and tend to exhibit greater aversion to paying. By contrast, credit card transactions, despite involving the same monetary outlay, reduce the perceived psychological loss (Qiu et al., 2025), which can lead to higher consumption. This effect is attributable to the mental accounting effect (Thaler, 1980). Consequently, the diminished perception of loss associated with digital payment methods may further stimulate spending and, in turn, heighten FV (Seldal & Nyhus, 2022; Qiu et al., 2025).

A closer examination of Table 1 brings us to the particular case of the study by Seldal and Nyhus (2022). As far as we know, these authors are the only ones who analyse an economically developed country (i.e., Norway) and who incorporate a self-perceived dimension into the assessment of FV.

Moreover, studies analysing traditional FI (Seldal & Nyhus, 2022; Hu et al., 2024; Verma & Chatterjee, 2025) suggest that it remains an important driving force of FV, particularly in countries where digital penetration within the financial system is still limited. These studies draw on indicators that capture access to, or use of, offline financial products—such as bank accounts or credit. However, this line of research is relatively scarce compared with the growing body of literature focusing exclusively on DFI. This gap underscores the need for studies that jointly analyse FI and DFI[1].

In summary, the review of prior literature highlights a major gap: the limited empirical evidence on the relationship between DFI and FV in economically developed countries. As far as we are aware, Seldal and Nyhus (2022) are the only authors who have examined this relationship in such a context. This paper contributes to the literature by offering new perspectives through a more detailed analysis of FV and by jointly examining DFI and offline FI. Against this backdrop, the present study aims to explore the relationship between DFI and FV among Spanish households using data from the 2021 wave of the GFD. Building on the findings of previous studies (see Table 1), the following two hypotheses are formulated:

Hypothesis 1 (H1). *Digital financial inclusion is negatively related to financial vulnerability.*

Hypothesis 2 (H2). *Digital financial inclusion has a stronger relationship with financial vulnerability than offline financial inclusion.*

3. Data and Methodology

3.1. Sample

The empirical analysis is based on Spanish microdata from the 2021 wave of the *Global Findex Database* (GFD), a large-scale survey compiled by the World Bank. This triennial dataset provides nationally representative data on FI and financial resilience covering almost 128,000 people in 123 worldwide economies. Specifically, respondents report their access to and use of a wide range of formal and informal financial services, as well as their engagement in financial practices that contribute to financial resilience (Demirgüç-Kunt et al., 2022; Verma & Chatterjee, 2025).

The sample size for this study consists of 1000 adults residing in Spain. Respondents were contacted by telephone between October and November 2021 (Demirgüç-Kunt et al., 2022) and were selected through a stratified sampling procedure. This approach ensured that the sampling units reflected the demographic and geographic diversity of Spanish regions. Households, and the individual respondents within them, were randomly selected. Prior to administering the survey, field agents verified that the selected person met the eligibility criterion regarding age. Respondents were required to be at least 16 years old (the minimum legal working age in Spain). Although some individuals therefore fall within the category of minors, all exceed the minimum legal age in Spain for providing consent to the processing of personal data for survey purposes.

To ensure representativeness, the GFD applies sampling weights that align the country-level sample with the demographic structure of the population. These weights were incorporated into all subsequent descriptive analyses and probit estimations (see Section 3.3 for further details). However, item non-response may still introduce bias into the results (Rubin, 1976; Ridder & Moffitt, 2007). Although removing observations affected by missing data is a straightforward solution, it entails a considerable risk of compromising representativeness and increasing bias (Rubin, 1976; Schafer & Graham, 2002). By contrast, imputation techniques replace missing values with plausible estimates based on the characteristics of the observed data (Lodder, 2013). In other words, imputation is performed at the population level rather than the unit level, aiming to generate accurate estimates based on averages, variances, and correlations with other variables (Lodder, 2013; Little & Rubin, 2019).

Since the proportion of missing data for the variables under analysis is below 10%, simple imputation techniques were applied to mitigate its impact (Rubin, 1976). Specifically, in all subsequent descriptive and econometric analyses, missing values were replaced using the following criteria: the mean of the observed data for continuous variables; the mode for binary variables; the median for ordinal variables with an even number of categories; and the central (or neutral) value for ordinal variables with an odd number of categories (Rubin, 1976).

3.2. Variables

Four dummy variables were constructed to assess FV, following the different measurement approaches highlighted in the literature. Two of these variables capture objective aspects of households' financial situation, based on their savings and consumption capacity (Fernández-López et al., 2023). The other two reflect subjective perceptions of individuals' difficulties in meeting their financial obligations (Seldal & Nyhus, 2022).

Regarding the objective variables, the first variable was derived from question FIN24, which asks respondents to imagine an emergency requiring payment of an amount equivalent to one-twentieth of the country's gross national income per capita within the next 30 days. This measure therefore captures the ability to cope with unforeseen events through accumulated savings (Loaba, 2022). Based on the responses, a dummy variable indicating a lack of financial resilience was coded as 1 for individuals unable to meet the specified amount, and 0 otherwise[2] (Table 2). This variable was computed for the full sample of 1000 individuals, enabling a distinction between "non-resilient" and "resilient" respondents, the latter being those who reported being able to cover the required amount.

Table 2. Definition of variables.

Name	Detail
Dependent variables	
Lacking financial resilience *	Cannot handle an emergency expense: (1) Cannot; (0) otherwise.
Lacking emergency savings * [*resilient*]	Source for emergency expense: (0) Savings; (1) Other sources (i.e., family, friends or relatives, salary advances, loans, selling assets, or other options).
Difficulties in 30-day emergency funds ** [*resilient*]	Obtaining emergency funds within 30 days is difficult: (1) Very/somewhat difficult; (0) not difficult.
Difficulties in 7-day emergency funds ** [*resilient*]	Obtaining emergency funds within 7 days is difficult: (1) Very/somewhat difficult; (0) not difficult.
Independent variables	
Making/receiving digital payments	Made or received digital payment: (1) Yes; (0) otherwise.
Invoice payment via Internet	Paid invoices online: (1) Yes; (0) otherwise.
Money transfer via Internet	Sent money online to a family member or friend: (1) Yes; (0) otherwise.
Online shopping via Internet	Purchased goods online: (1) Yes; (0) otherwise.
Digital payments via Internet [1]	Count of online payment types, from 0 (none) to 3 (invoice payment + money transfers + online shopping).
In-store payment via mobile phone	Paid in-store by mobile: (1) Yes; (0) otherwise.
Utility payment via mobile phone	Paid utilities by mobile: (1) Yes; (0) otherwise.
Digital payments via mobile phone [1]	Count of mobile payment types, from 0 (none) to 2 (in-store purchases + utilities).
Control variables	
Age [2]	Age in years.
Gender	(1) Female; (0) male.
Educational attainment [1]	Highest educational level achieved: (1) Primary or below, (2) secondary, and (3) tertiary or higher.
Income [1]	Household income quintile, from 1 (lowest) to 5 (highest).
Job situation	(1) Employee; (0) otherwise.
Debit card ownership/use [1]	Own/use of debit card in the last 12 months: (2) Owns and uses; (1) owns but not used; (0) does not own.
Credit card ownership/use [1]	Own/use of credit card in the last 12 months: (2) Owns and uses; (1) owns but not used; (0) does not own.

Notes: Most variables in Table 2 are binary (0, 1), while others are ordinal ([1]) or continuous ([2]). The * and ** symbols indicate whether the FI variable is objective or subjective, respectively. All variables refer to the full sample, except those marked as [*resilient*], which are computed only for that subsample.

For the subsample of "resilient" individuals, a second objective variable was constructed to capture the availability of emergency savings. This variable (*lacking emergency savings*) was coded as 0 when respondents stated that they could use their own savings to cover the hypothetical emergency, and as 1 when they would need to rely on alternative sources. This variable serves as a proxy for the availability of emergency savings, a widely examined measure in the FV literature (e.g., Friedline & West, 2016; Cardona-Montoya et al., 2022).

Regarding the subjective variables, and following the criteria established by Fernández-López et al. (2023), two dummy variables were constructed to capture individuals' self-perceived FV. These variables identify respondents who reported that obtaining the required emergency funds would be somewhat difficult or very difficult (coded as 1), as opposed to not at all difficult (coded as 0). The two indicators differ only in the time frame considered: the first refers to the ability to obtain the amount within the next 30 days, and the second refers to the ability to obtain it within the next 7 days.

To assess DFI, we focused on usage dimension, following previous literature. Specifically, DFI represents the digital manifestation of offline FI, as it reflects the extent to which individuals are able to undertake financial actions through digital channels (Seldal & Nyhus, 2022; Verma & Chatterjee, 2025). These actions cannot be guaranteed merely by providing access to basic financial products; rather, it is essential to examine how frequently and regularly individuals use these products (Wang & Guan, 2017; Koomson et al., 2020). As emphasised by Wang and Guan (2017), DFI indicators should capture basic financial behaviours, which can be classified into three domains: recurring expenditures, savings, and consumer purchases. In this study, three measures derived from questions in the GFD are used to approximate these domains. The details of these measures are outlined below.

The first measure, *making/receiving digital payments*, is a dummy variable coded as 1 when the individual has made or received at least one digital payment, and 0 otherwise (payments dimension). The remaining two variables are ordinal and capture the diversity of digital payment types conducted via Internet or mobile banking, following the criteria established by Loaba (2022) and Seldal and Nyhus (2022). The variable for *digital payments via Internet* aggregates affirmative responses (coded 1 for "yes", 0 otherwise) to three items indicating whether the respondent used the Internet for (1) invoice payments (recurring expenditures dimension), (2) sending money to a family member or friend (savings dimension), and (3) online shopping (consumer purchases dimension). Similarly, the variable for *digital payments via mobile phone* is constructed by summing affirmative responses to two items capturing whether the respondent used a mobile phone to pay for: (1) in-store purchases (consumer purchases dimension) and (2) utility bills (recurring expenditures dimension).

Additionally, a set of commonly recognized sociodemographic and economic determinants of FV were included as control variables. In line with previous studies by Hu et al. (2024) and Verma and Chatterjee (2025), two variables were incorporated to capture offline FI. Within the Spanish sample, the only available indicators of access to financial products through offline channels relate to the ownership and use of debit or credit cards[3].

3.3. Model Specification

Given that FV was measured using dichotomous variables, *probit* regression models were estimated. This method captures non-linear relationship between the dependent variable and a set of explanatory variables (Long & Freese, 2014). Equation (1) presents the basic specification of the model:

$$Pr\ (FV_i = 1 \mid X) = \Phi\ (\beta_0 + \beta_1 DFI_i + \beta_2 Control_i) \tag{1}$$

where FV_i denotes the probability that individual i experiences financial hardship. *DFI* represents the set of key independent variables related to the use of digital financial services, which were introduced alternatively across model specifications. To mitigate potential omitted-variable bias, the control variables (*Control*) listed in Table 2 were included. Age was incorporated in both its linear and quadratic forms to explore possible non-linear relationships between age and FV.

The coefficient of interest, β_1, is expected to be negative, consistent with the evidence reported in previous studies summarized in Table 1. Finally, Φ denotes the cumulative normal distribution function (Long & Freese, 2014).

4. Results and Discussion

4.1. Descriptive Analysis

Considering objective FV, 11% of the sample are classified as non-resilient, reporting insufficient financial resources to cope with unexpected expenses (Figure 2). By contrast, 89% indicate that they are able to manage such contingencies and are therefore considered financially resilient. Among this group, approximately half rely primarily on personal savings, whereas the remaining 39% would need to depend on alternative sources, such as support from family or friends, loans, or salary advances.

The presence of savings thus constitutes a critical determinant of financial resilience. It substantially shapes individuals' capacity to handle adverse economic situations and to prepare for unforeseen financial demands.

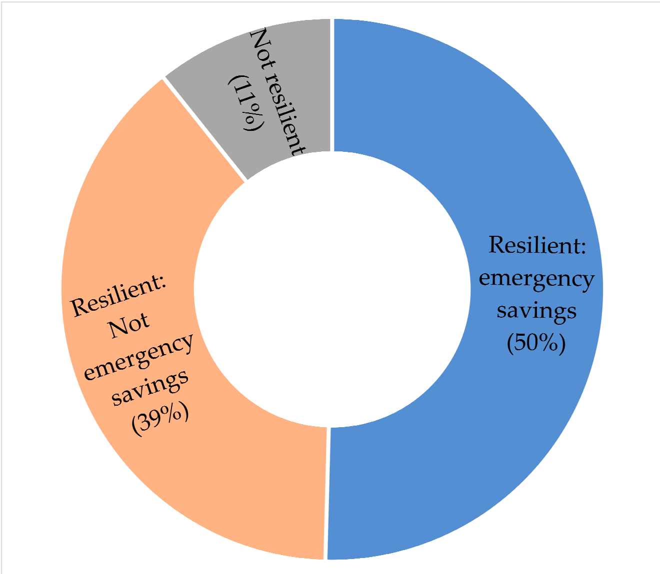

Figure 2. Financial resilience and emergency savings (% of individuals).

From a subjective perspective, concerning perceived difficulties in accessing emergency funds (Figure 3), approximately one-third of individuals classified as financially resilient report that they would face considerable challenges—whether somewhat or very difficult—in covering an unexpected expense within either a 30-day or 7-day period. In contrast, regardless of whether emergency funds would be drawn from savings or alternative sources, around two-thirds of respondents do not anticipate any difficulty in meeting such expenses.

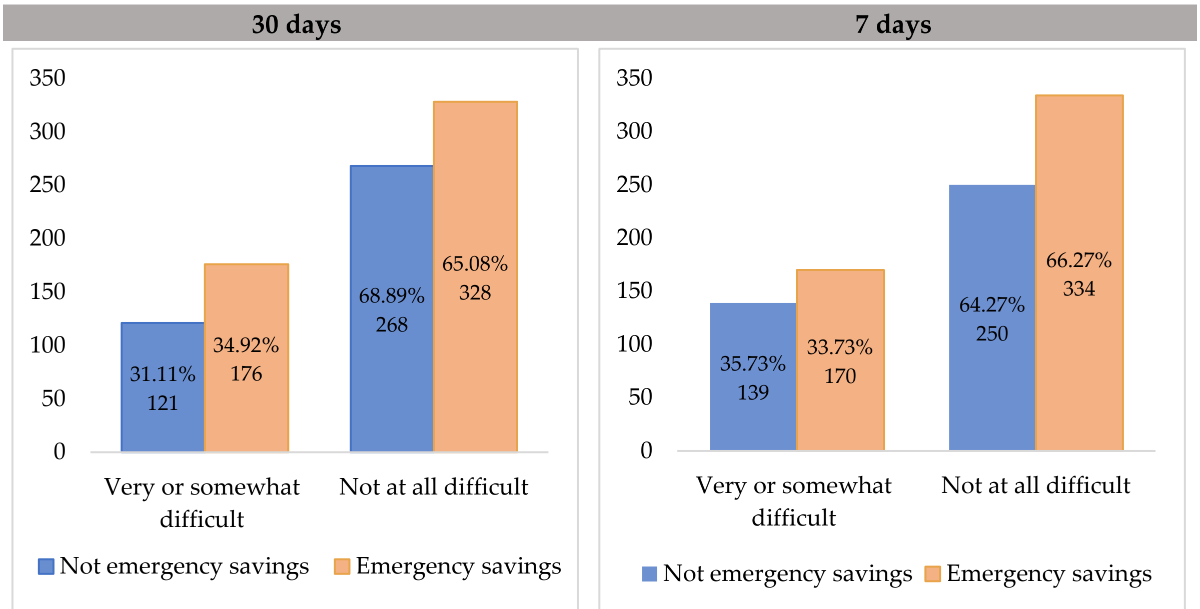

Figure 3. Perceived difficulties in obtaining 30-day and 7-day emergency funds (% and number of individuals).

Taken together, the descriptive evidence yields three main conclusions. First, financial difficulties persist even among individuals classified as financially resilient, indicating that FV varies considerable within this group. Second, the self-perceived difficulty increases slightly—particularly among those who must combine sources other than their own savings to constitute an emergency fund—when the timeframe for securing funds is shortened to 7 days. This evidence suggests that financial pressure intensifies as the deadline approaches, thereby limiting individuals' capacity to respond to unexpected events. Third, perceived difficulty in facing an unforeseen expense is remarkably similar for individuals with emergency savings and those without. Although somewhat counterintuitive, this finding highlights the complexity of how individuals assess their financial well-being, as such assessment reflect not only objective financial conditions but also subjective perceptions and psychological factors.

Regardless of their objective or subjective FV status, almost all respondents (99%) have made or received at least one digital payment (*Making/receiving digital payments*), as shown in Figure 4. However, the adoption of digital tools is far less widespread when considering the execution of specific financial transactions. Thus, considering Internet-based payments—namely invoice payments, money transfers, and online shopping—14% of the population has not used the Internet for any of these operations, 31% have used it for only one type of payment, and only 23% have used it for all three. The adoption of mobile phones for financial transactions (*Digital payments via mobile phone*) is even more limited: 63% of respondents report not having used their mobile phone for either in-store purchases or utility payments, compared with 33% who have used it for one of these payments and only 4% who used it for both.

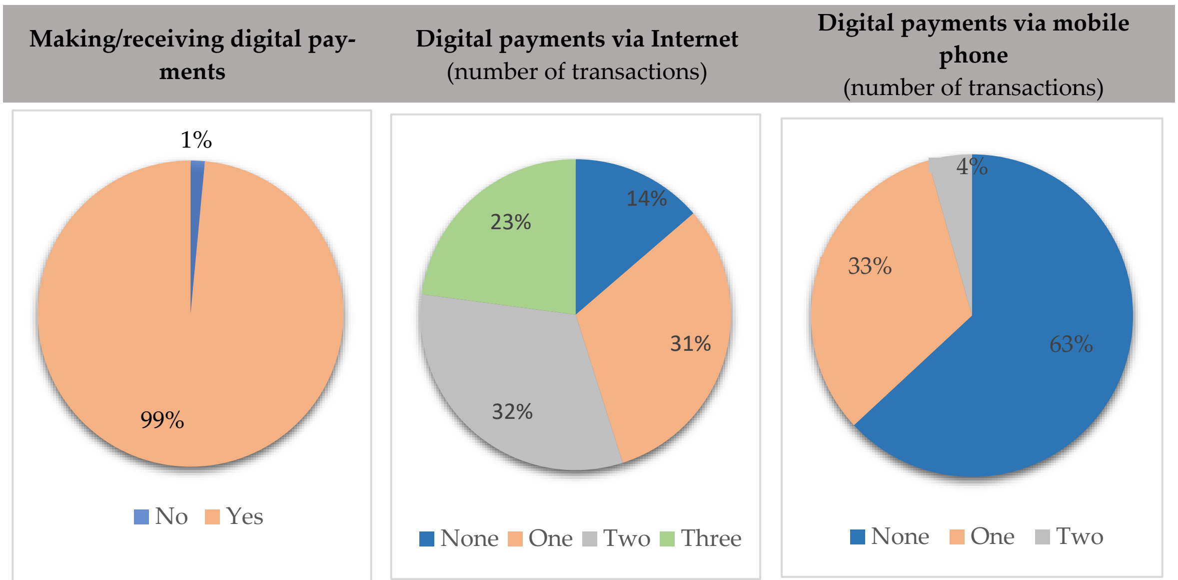

Figure 4. DFI (% of individuals).

These figures indicate that, as of 2021, digital platforms—such as the Internet and, particularly, mobile phones—had not yet been widely adopted as routine channels for conducting everyday financial transactions among a considerable share of the Spanish population.

A joint descriptive analysis of FV and DFI is shown in Table 3. It reports the percentage distribution of respondents according to their level of FV and the number of financial transactions conducted via Internet or mobile devices. In addition, the association between these ordinal DFI variables and the four binary indicators of FV was examined. To this end, Pearson's non-parametric Chi-square (χ^2) test of independence was employed, assessing how much the observed cell frequencies deviate from those expected under independence. The χ^2 statistic is computed as shown in Equation (2):

$$\chi^2 = \sum_{i=1}^{R} \sum_{j=1}^{C} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \tag{2}$$

where O_{ij} denotes the observed frequency in the cell at row i and column j, and E_{ij} is the corresponding expected frequency under independence assumption. Expected frequencies were obtained by multiplying the total count in row i by the total count in column j and dividing the product by the overall sample size.

The resulting χ^2 statistic was compared with the theoretical Chi-square distribution with $(R-1)(C-1)$ degrees of freedom. A statistically significant value leads to rejection of the null hypothesis of independence, indicating that the variables represented in row i and column j are associated.

Table 3. Distribution of respondents considering FV and DFI.

		Number of Different Digital Payments								
		Internet					**Mobile Phone**			
		0	**1**	**2**	**3**	χ^2	**0**	**1**	**2**	χ^2
Lacking financial resilience	No (0)	108 78.83%	283 90.13%	286 89.38%	216 94.32%	**21.98**	554 87.80%	299 92.00%	40 90.91%	4.09
	Yes (1)	29 21.17%	31 9.87%	34 10.63%	13 5.68%		77 12.20%	26 8.00%	4 9.09%	
Lacking emergency savings	No (0)	59 54.63%	190 67.14%	150 52.45%	105 48.61%	**20.55**	295 53.25%	186 62.21%	23 57.50%	**6.35**
	Yes (1)	49 45.37%	93 32.86%	136 47.55%	111 51.39%		259 46.75%	113 37.79%	17 42.50%	
Difficulties in 30-day emergency funds	No (0)	72 66.67%	169 59.72%	198 69.23%	157 72.69%	**10.52**	393 70.94%	182 60.87%	21 52.50%	**12.69**
	Yes (1)	36 33.33%	114 40.28%	88 30.77%	59 27.31%		161 29.06%	117 39.13%	19 47.50%	
Difficulties in 7-day emergency funds	No (0)	71 65.74%	183 64.66%	179 62.59%	151 69.91%	3.01	376 67.87%	186 62.21%	22 55.00%	4.75
	Yes (1)	37 34.26%	100 35.34%	107 37.41%	65 30.09%		178 32.13%	113 37.79%	18 45.00%	

Note: Values in bod indicate that the calculated χ^2 statistic is statistically significant at the 5% level.

Results from Pearson's χ^2 test of independence reveal statistically significant differences in FV across levels of DFI (see Table 3). As the range of transactions conducted online or via mobile devices increases, the proportion of individuals lacking financial resilience decreases. However, this correlation is statistically significant only for Internet-based payments. A similar pattern emerges for the absence of emergency savings: the percentage of individuals without savings falls as the diversity of mobile-based operations rises. Unexpectedly, this pattern shifts when considering specific types of Internet-based payments. In this case, the relationship between the lack of emergency funds and digital transactions channels remains statistically significant, regardless of the platform used.

From a subjective standpoint, individuals who have not performed any online transaction report greater difficulty in accessing emergency funds than those who operate online. Conversely to expectations, however, individuals who engage in a greater variety of transactions via mobile devices face greater challenges in saving for unforeseen expenses.

Turning to the main sociodemographic and economic characteristics, the data indicate a gender-balanced sample, with women representing 49.93% of respondents (Table 4). The average age is close to 49 years. Most individuals (73.29%) have completed at least secondary education, whereas smaller percentages have completed tertiary education (6.19%) or only primary education or less (20.51%). Among those surveyed, 55.97% are employed.

The use of debit cards is highly prevalent: 83.28% of respondents report having used a debit card within the past 12 months. In contrast, credit card usage is less widespread (46.29%), and 10.31% of respondents report not using them despite having at least one available.

Table 4. Summary statistics for the control variables.

Variable		Mean Values
Age		48.60 (years)
Gender: female		49.93%
Educational attainment	(1) Primary or less	20.51%
	(2) Secondary	73.29%
	(3) Tertiary or higher	6.19%
Income	(1) Poorest quintile (bottom 20%)	19.96%
	(2) Second quintile (20–40%)	20.00%
	(3) Middle quintile (40–60%)	20.02%
	(4) Fourth quintile (60–80%)	19.86%
	(5) Richest quintile (top 20%)	20.16%
Job situation: employee		55.97%
Credit card ownership/use	(0) Does not own	43.39%
	(1) Owns but not used	10.31%
	(2) Owns and uses	46.29%
Debit card ownership/use	(0) Does not own	16.72%
	(1) Owns but not used	0.00%
	(2) Owns and uses	83.28%

Note: The GFD does not provide country specific cut off values for the income-quintile variable.

Pearson correlation coefficients between the variables (Table 5) are relatively low. The highest significant values are observed among the FV and DFI variables. As these variables are derived from the same underlying constructs, they are not included simultaneously in the subsequent regression models.

4.2. Multivariate Analysis

Estimating the models specified in Equation (1) provides deeper insight into the relationship between FV and DFI. Tables 6 and 7 report the marginal effects for the DFI variables as well as for the control variables. Each model incorporates the full set of control variables and, alternatively, one of the three DFI indicators. This procedure was applied to each of the four FV measures, yielding a total of 12 estimated models. Credit card ownership/use was selected as a proxy for offline FI.

Prior to estimation, potential multicollinearity was assessed by calculating the Variance Inflation Factors (VIF). With the exception of age and its squared term, all VIF values were below 2, well beneath the recommended threshold of 6 suggested by Hair et al. (1998). These results indicate that multicollinearity does not pose a concern in the data.

The models examining the lack of financial resilience display an acceptable fit, with McFadden's R^2 values ranging from 0.14 to 0.15. By contrast, the remaining models exhibit substantially weaker fit ($R^2 \approx 0.03$–0.04), indicating limited explanatory power (Hair et al., 1998). This suggests that a considerable share of the variation in FV may be driven by additional unobserved factors, beyond the variables included in the analysis. However, this paper adopts an "explanatory modelling" approach (Shmueli, 2010), with the objective being explanatory rather than predictive. Consequently, low R^2 values does not necessarily undermine the analysis, provided that the estimated coefficients are statistically significant, robust, and consistent with previous literature (Freedman, 2009; Wooldridge, 2010). Importantly, across all models, the Wald statistics confirm the joint significance of the independent variables.

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Table 5. Correlation matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	Lacking financial resilience	1																		
(2)	Lacking emergency savings	**1**	1																	
(3)	Difficulties in 30-day emergency funds	−0.051	−0.051	1																
(4)	Difficulties in 7-day emergency funds	**0.082**	**0.082**	**0.194**	1															
(5)	Making/receiving digital payments	**−0.136**	**−0.070**	**−0.095**	**−0.109**	1														
(6)	Invoice payment via Internet	**−0.071**	**−0.114**	**0.145**	**0.102**	**−0.153**	1													
(7)	Money transfer via Internet	**0.071**	−0.016	**−0.148**	−0.018	**−0.122**	**0.067**	1												
(8)	Online shopping via Internet	−0.062	**−0.105**	0.034	−0.021	**−0.118**	**0.229**	**0.111**	1											
(9)	Digital payments via Internet	0.036	**0.130**	−0.020	−0.038	**0.202**	**−0.659**	**−0.609**	**−0.674**	1										
(10)	Payment for in-store purchases via mobile phone	**0.135**	**0.104**	**−0.113**	−0.057	**−0.119**	**−0.071**	**0.192**	0.059	**−0.094**	1									
(11)	Utility payment via mobile phone	−0.003	−0.011	−0.065	−0.014	−0.035	**0.089**	**0.120**	0.041	**−0.126**	**0.152**	1								
(12)	Digital payments via mobile phone	**−0.115**	**−0.089**	**0.114**	0.045	**0.120**	0.015	**−0.199**	**−0.074**	**0.133**	**−0.885**	**−0.642**	1							
(13)	Age	−0.024	**−0.105**	0.000	**−0.066**	0.010	0.022	**0.106**	**0.115**	**−0.120**	**0.076**	0.057	**−0.082**	1						
(14)	Gender	−0.004	0.024	−0.027	0.020	**0.088**	0.004	0.016	−0.049	0.016	**−0.066**	−0.040	**0.068**	0.023	1					
(15)	Educational attainment	0.055	**0.139**	**−0.122**	−0.047	**0.081**	**−0.072**	−0.020	**−0.092**	**0.096**	**0.078**	0.055	**−0.094**	**−0.339**	0.053	1				
(16)	Income	**−0.073**	−0.010	**−0.160**	**−0.092**	0.056	0.054	**−0.082**	0.027	0.002	−0.041	**0.082**	−0.004	0.053	**0.137**	**0.234**	1			
(17)	Employee	**−0.066**	**−0.089**	**0.088**	−0.030	**0.076**	0.022	−0.033	**0.144**	**−0.066**	**0.066**	0.003	−0.050	**0.297**	**−0.135**	**−0.219**	−0.058	1		
(18)	Debit card ownership/use	0.021	0.053	−0.042	**−0.067**	**0.339**	**−0.091**	0.059	**−0.134**	**0.082**	−0.006	−0.017	0.008	0.006	**0.123**	**0.098**	−0.035	−0.054	1	
(19)	Credit card ownership/use	**−0.077**	−0.051	0.023	−0.062	**0.173**	0.030	**−0.082**	0.007	0.027	**−0.096**	−0.064	**0.110**	0.050	0.048	−0.032	**0.076**	0.031	0.033	1

Note: Boldface indicates statistical significance at the 5% level.

Table 6. DFI and objective FV: marginal effects.

		Lacking Financial Resilience			Lacking Emergency Savings		
		m1	**m2**	**m3**	**m4**	**m5**	**m6**
Making/receiving digital payments		−0.471 *** (0.142)			−0.314 * (0.156)		
Digital payments via Internet [*Ref. (0) None*]	(1) One		−0.124 *** (0.028)			−0.004 (0.070)	
	(2) Two		−0.102 *** (0.031)			0.169 * (0.068)	
	(3) Three		−0.132 *** (0.027)			0.128 † (0.071)	
Digital payments via mobile phone [*Ref. (0) None*]	(1) One			−0.052 * (0.026)			−0.098 * (0.047)
	(2) Two			−0.053 (0.052)			−0.018 (0.123)
Offline FI with credit card [*Ref. 0 Does not own*]	(1) Owns but not used	0.005 (0.044)	−0.001 (0.040)	−0.013 (0.041)	−0.022 (0.078)	−0.032 (0.076)	−0.022 (0.077)
	(2) Owns and uses	−0.03 (0.028)	−0.034 (0.027)	−0.045 (0.028)	−0.035 (0.046)	−0.031 (0.045)	−0.037 (0.046)
Gender: female		−0.014 (0.026)	−0.020 (0.025)	−0.025 (0.027)	0.048 (0.045)	0.043 (0.044)	0.042 (0.045)
Age		0.0001 (0.005)	−0.001 (0.005)	−0.001 (0.005)	0.0001 (0.009)	−0.002 (0.009)	−0.002 (0.009)
Age squared		0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Educational attainment [*Ref. (1) Primary or less*]	(2) Secondary	−0.016 (0.035)	−0.035 (0.037)	−0.047 (0.040)	0.261 *** (0.067)	0.249 *** (0.068)	0.247 *** (0.069)
	(3) Tertiary or higher	−0.053 (0.038)	−0.061 † (0.035)	−0.069 * (0.035)	0.126 (0.094)	0.100 (0.096)	0.110 (0.094)
Income quintile [*Ref. (1) Poorest quintile (bottom 20%)*]	(2) Second quintile (20–40%)	−0.098 *** (0.025)	−0.105 *** (0.023)	−0.105 *** (0.024)	−0.015 (0.081)	−0.034 (0.08)	−0.020 (0.08)
	(3) Middle quintile (40–60%)	−0.082 ** (0.028)	−0.080 ** (0.028)	−0.076 ** (0.029)	−0.028 (0.081)	−0.028 (0.079)	−0.027 (0.080)
	(4) Fourth quintile (60–80%)	−0.095 ** (0.030)	−0.092 ** (0.030)	−0.093 ** (0.031)	−0.051 (0.076)	−0.055 (0.074)	−0.051 (0.074)
	(5) Richest quintile (top 20%)	−0.126 *** (0.030)	−0.121 *** (0.029)	−0.129 *** (0.030)	−0.036 (0.077)	−0.042 (0.076)	−0.039 (0.075)
Job situation: employee		0.024 (0.029)	0.035 (0.026)	0.039 (0.028)	0.049 (0.050)	0.047 (0.049)	0.059 (0.050)
Observations		1000	1000	1000	893	893	893
Pseudolikelihood		−343.88	−340.03	−354.12	−564.68	−555.28	−562.37
Wald χ^2 (d.f.)		60.41 (13)	63.37 (15)	42.81 (14)	23.60 (13)	32.27 (15)	28.19 (14)
R^2 McFadden		0.14	0.15	0.12	0.04	0.06	0.05
Akaike criterion (d.f.)		715.75 (14)	712.05 (16)	738.23 (15)	1157.36 (14)	1142.55 (16)	1154.74 (15)

Notes: Table 6 reports the marginal effects from the *probit* models. *d.f.* denotes degrees of freedom. Robust standard errors are shown in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Overall, the estimates indicate that higher levels of DFI are associated with a lower probability of experiencing FV. This finding is broadly consistent with the results reported in previous studies (e.g., Loaba, 2022; Seldal & Nyhus, 2022; Xu et al., 2024; Verma & Chatterjee, 2025) and supports the acceptance of the first proposed hypothesis. However, this relationship does not hold uniformly across all specifications and varies according to the specific variables examined.

Notably, the variable associated with making or receiving digital payments exhibits a negative association with FV across all estimated models. This finding is consistent with the theoretical propositions underpinning the financial capability framework proposed by Sherraden (2013). Accordingly, participation in digital payments may serve as a proxy for access to financial products that enhance individuals' capacity to manage their financial resources efficiently. Improved financial management is expected to reduce indebtedness

(Qiu et al., 2025) and to strengthen resilience in the face of unexpected expenditures (Verma & Chatterjee, 2025).

Table 7. DFI and subjective FV: marginal effects.

		Difficulties in 30-Day Emergency Funds			Difficulties in 7-Day Emergency Funds		
		m1	m2	m3	m4	m5	m6
Making/receiving digital payments		−0.537 *** (0.096)			−0.531 *** (0.095)		
Digital payments via Internet [*Ref. (0) None*]	(1) One		0.088 (0.070)			−0.014 (0.068)	
	(2) Two		0.034 (0.068)			0.064 (0.070)	
	(3) Three		0.027 (0.072)			−0.091 (0.068)	
Digital payments via mobile phone [*Ref. (0) None*]	(1) One			0.080 † (0.046)			0.066 (0.046)
	(2) Two			0.162 (0.118)			−0.048 (0.091)
Offline FI with credit card [*Ref. 0 Does not own*]	(1) Owns but not uses	−0.019 (0.069)	−0.034 (0.069)	−0.032 (0.068)	−0.149 ** (0.057)	−0.149 ** (0.056)	−0.162 ** (0.055)
	(2) Owns and uses	0.034 (0.044)	0.020 (0.044)	0.016 (0.044)	−0.045 (0.044)	−0.048 (0.043)	−0.056 (0.043)
Gender: female		0.002 (0.043)	−0.004 (0.043)	−0.011 (0.043)	0.027 (0.042)	0.025 (0.042)	0.025 (0.042)
Age		−0.008 (0.008)	−0.009 (0.008)	−0.010 (0.008)	0.006 (0.008)	0.004 (0.008)	0.004 (0.008)
Age squared		0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Educational attainment [*Ref. (1) Primary or less*]	(2) Secondary	−0.127 † (0.073)	−0.119 (0.073)	−0.104 (0.073)	−0.075 (0.073)	−0.077 (0.072)	−0.066 (0.074)
	(3) Tertiary or higher	−0.122 (0.074)	−0.111 (0.076)	−0.098 (0.077)	−0.080 (0.080)	−0.087 (0.078)	−0.073 (0.081)
Income quintile [*Ref. (1) Poorest quintile (bottom 20%)*]	(2) Second quintile (20–40%)	−0.024 (0.071)	−0.017 (0.073)	−0.025 (0.072)	−0.024 (0.072)	−0.040 (0.070)	−0.022 (0.073)
	(3) Middle quintile (40–60%)	−0.110 † (0.063)	−0.097 (0.065)	−0.094 (0.065)	−0.011 (0.073)	−0.020 (0.071)	0.003 (0.074)
	(4) Fourth quintile (60–80%)	−0.157 ** (0.059)	−0.149 * (0.061)	−0.153 * (0.061)	−0.083 (0.066)	−0.091 (0.064)	−0.075 (0.067)
	(5) Richest quintile (top 20%)	−0.154 * (0.063)	−0.155 * (0.063)	−0.156 * (0.063)	−0.088 (0.068)	−0.100 (0.066)	−0.088 (0.069)
Job situation: employee		−0.061 (0.049)	−0.051 (0.049)	−0.057 (0.049)	0.004 (0.046)	0.007 (0.046)	0.012 (0.046)
Observations		893	893	893	893	893	893
Pseudolikelihood		−545.78	−548.54	−546.26	−545.47	−543.29	−547.35
Wald χ^2 (d.f.)		33.82 (13)	22.80 (15)	24.36 (14)	31.26 (13)	25.13 (15)	19.41 (14)
R^2 McFadden		0.04	0.04	0.04	0.03	0.03	0.03
Akaike criterion (d.f.)		1119.56 (14)	1129.08 (16)	1122.52 (15)	1118.94 (14)	1118.58 (16)	1124.70 (15)

Notes: Table 7 reports the marginal effects from the probit models. *d.f.* denotes degrees of freedom. Robust standard errors are shown in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

At the empirical level, individuals who engage in digital payments exhibit a 47.1% lower probability of lacking financial resilience and a 31.4% lower probability of experiencing difficulties in obtaining emergency funds. These marginal effects—defined as the difference between the estimated probabilities of being financially vulnerable or not—are illustrated graphically in Figure 5a. Among the DFI indicators, *Making/receiving digital payments* yields the most robust and consistent results across the model specifications.

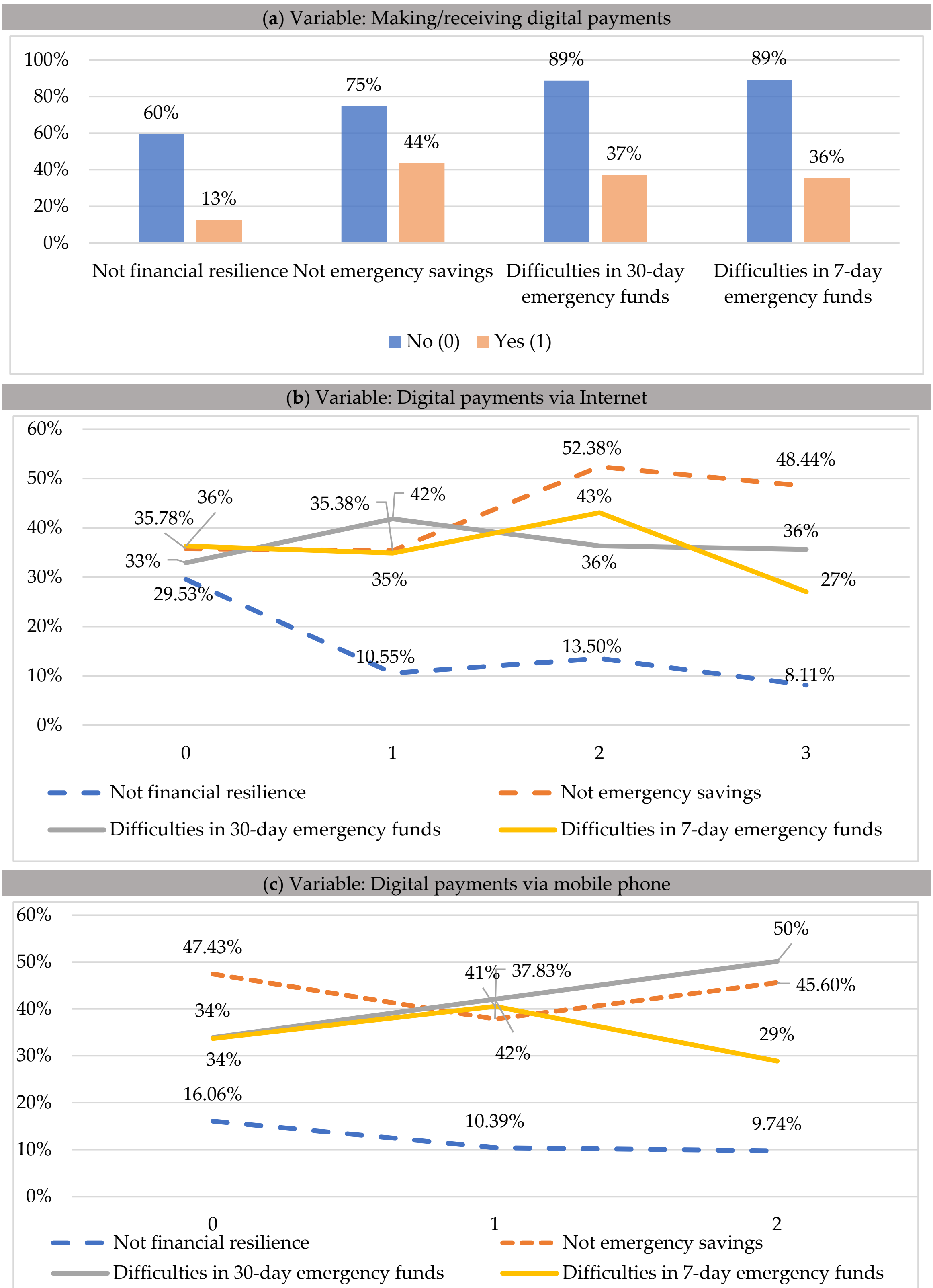

Figure 5. Estimated probabilities of FV based on DFI variables.

The use of the Internet for digital payments (*Digital payments via Internet*) exhibits an ambiguous relationship with FV, as shown in Table 6 and Figure 5b. Although all three usage levels (one, two, and three types of payment) are associated with statistically significant reductions in the probability of lacking financial resilience (Table 6), in line with the financial capability framework, engaging in two or more types of online transactions increases the likelihood of lacking emergency savings (Figure 5b). This positive relationship, also observed by Seldal and Nyhus (2022) in another economically developed country, suggests that the use of certain digital channels may become counterproductive, deteriorating users' objective financial conditions and heightening their perceived financial constraints. This effect appears particularly pronounced in the short term, as evidenced by the non-significant result for perceived difficulties over a 30-day horizon.

Consistent with the theoretical framework of bounded rationality (Simon, 2000), individuals are cognitively predisposed to simplify decision-making in contexts where processing all relevant information is infeasible. Online financial transactions typically require minimal effort and time, often involving only a few clicks. Such procedural simplicity may foster a false sense of security (Qiu et al., 2025), thereby encouraging insufficiently deliberated financial choices with adverse consequences for both objective and subjective FV (Seldal & Nyhus, 2022; Qiu et al., 2025).

The use of mobile devices for digital payments (*Digital payments via mobile phone*) yields results somewhat similar to those observed for Internet-based payments, although the patterns are less clearly defined. Such payments are associated with a lower probability of lacking financial resilience or emergency savings. However, these relationships cease to be statistically significant when individuals engage in two types of transactions (namely, in-store and utility payments). Moreover, while a negative association is observed with objectively measured FV (Table 6), no statistically significant effects emerge when FV is assessed from a subjective perspective (Table 7). Notably, Figure 5c indicates a potential relationship between more frequent mobile-based digital payments and a greater perceived difficulty in accessing emergency funds over the longest timeframe (30 days).

Although sociodemographic, economic, and offline FI control variables were included, only a limited number exhibit statistically significant marginal effects. Notably, education attainment yields mixed results. While completing tertiary education increases the likelihood of being financially resilient, completing secondary education—compared to only primary education—appears to raise the probability of lacking emergency savings.

Income is negatively related to FV when measured in terms of financial resilience and perceived difficulties in accessing emergency funds within a 30-day horizon. Specifically, higher income levels reduce the risk of lacking financial resilience and alleviate perceived difficulties in accessing emergency funds over this period. However, income does not appear to strengthen individuals' confidence in their financial capacity, nor does it significantly mitigate perceived challenges in accessing emergency funds in the very short term (seven days).

By contrast, the coefficients associated with age, gender, and job situation do not exhibit statistically significant relationships with FV. Similar outcomes are obtained for the offline FI regressor (namely, credit card ownership/use), which may suggest a diminished explanatory power of this traditional financial product relative to channels facilitating digital financial interactions, thus supporting the second hypothesis formulated in this paper. Nonetheless, credit card ownership is found to reduce the likelihood of perceiving difficulties in accessing emergency funds within seven-day horizon. A plausible explanation is that credit card ownership provides individuals immediate access to liquidity, thereby easing perceived constraints in meeting urgent financial needs and functioning as a short-term financial safety net during emergencies.

In summary, the estimated marginal effects indicate that DFI, measured through making or receiving digital payments, is associated with lower FV from both objective and subjective perspectives. From a subjective standpoint, the probability of reporting difficulties in accessing emergency funds decreases by approximately 53% among individuals who have engaged in digital payments. From an objective standpoint, statistically significant decreases are also observed, albeit smaller: a 47% decrease in the probability of lacking financial resilience and a 31% decrease in the probability of lacking emergency savings. Collectively, these findings suggest that DFI contributes to enhancing the financial resilience of Spanish households. In so doing, the present study is among the few to provide empirical evidence of this relationship within the context of an economically developed economy. Moreover, the results lend further support to the financial capability framework (Sherraden, 2013), indicating that DFI mitigates FV by enhancing access to digital financial products and services that are more affordable and accessible than traditional financial channels.

However, when the analysis accounts for the specific digital channels through which financial transactions are conducted, the relationship between DFI and FV becomes more ambiguous. Our findings indicate that using the Internet as a channel for financial transactions is associated with an increased likelihood of lacking emergency savings. In other words, digital payments via the Internet may undermine individuals' ability to save. A plausible explanation is that digital financial channels reduce the psychological "pain of paying" relative to offline channels or cash (Qiu et al., 2025; Seldal & Nyhus, 2022), thereby fostering impulsive consumption and overspending (Qiu et al., 2025).

4.3. Endogeneity Issues

To assess the robustness of the results, the potential presence of endogeneity in the main regressors was examined. Endogeneity constitutes a primary concern in empirical research, as it induces biased and inconsistent estimators (Wooldridge, 2010). Although this problem is not specific to any particular data structure, it is especially challenging to identify in strictly cross-sectional designs. In such designs, dependent and independent variables are observed at a single point in time, making it difficult the distinction between simultaneity and causal relationships (Willard, 2012).

Previous studies have largely relied on instrumental variable techniques, which entails substantial limitations, particularly when it comes to identifying instruments that are both theoretically valid and available in the dataset (Falkenström et al., 2023). To overcome these constraints, a semiparametric method that does not require external instruments was adopted, namely the Gaussian Copula (GC) approach proposed by Park and Gupta (2012). Following confirmation of the non-normality of the main regressors, a *GC* term was constructed for each DFI variable using the following expression:

$$GC = \Phi^{-1}\lceil \mathrm{H}(\mathrm{X}) \rceil \quad (3)$$

where Φ^{-1} stands for the inverse of the standard normal cumulative distribution function and $\mathrm{H}(\mathrm{X})$ represents the empirical cumulative density function of each potentially endogenous variable.

The marginal effects obtained after introducing an additional control variable—added separately in each estimation derived from Equation (1) to address potential endogeneity in each DFI indicator—are reported in Tables 8 and 9.

After accounting for potential endogeneity-related distortions, the estimation results continue to indicate a negative relationship between DFI—measured through digital payment usage—and FV from both objective and subjective perspectives. Turning to variables related to Internet- and mobile-based payments, coefficients lose much of their statistical significance, particularly for subjective measures of FV. However, positive associations consistent with the bounded rationality framework (Simon, 2000) persists between Internet-based payments and the lack of emergency savings, albeit with weak statistical significance. By contrast, these relationships become negative when mobile-based payments are considered. Finally, the results for the control variables remain largely unchanged, with statistically significant evidence continuing to be observed for educational attainment and income.

Table 8. DFI and objective FV: marginal effects including GC.

		Lacking Financial Resilience			Lacking Emergency Savings		
		m1	m2	m3	m4	m5	m6
Making/receiving digital payments (including GC)		−0.445 ** (0.163)			−0.283 (0.179)		
Digital payments via Internet (including GC) [*Ref. (0) None*]	(1) One		−0.068 (0.043)			0.015 (0.094)	
	(2) Two		−0.017 (0.057)			0.195 † (0.110)	
	(3) Three		−0.032 (0.073)			0.169 (0.155)	
Digital payments via mobile phone (including GC) [*Ref. (0) None*]	(1) One			−0.117 ** (0.036)			−0.162 * (0.072)
	(2) Two			−0.115 *** (0.027)			−0.120 (0.145)
Offline FI with credit card [*Ref. 0 Does not own*]	(1) Owns but not used	−0.021 (0.041)	−0.048 (0.035)	−0.070 † (0.038)	−0.047 (0.075)	−0.065 (0.070)	−0.062 (0.073)
	(2) Owns and uses	−0.014 (0.042)	−0.034 (0.036)	−0.054 (0.035)	−0.042 (0.078)	−0.052 (0.072)	−0.053 (0.077)
Gender: female		−0.015 (0.026)	−0.019 (0.025)	−0.014 (0.026)	0.047 (0.045)	0.044 (0.044)	0.047 (0.044)
Age		0.0003 (0.005)	−0.0006 (0.005)	−0.001 (0.005)	0.0003 (0.009)	−0.002 (0.009)	−0.002 (0.009)
Age squared		0.00003 (0.0001)	0.0003 (0.005)	0.00003 (0.0001)	−0.00001 (0.0001)	−0.00001 (0.0001)	−0.00001 (0.0001)
Educational attainment [*Ref. (1) Primary or less*]	(2) Secondary	−0.011 (0.034)	−0.027 (0.035)	−0.048 (0.041)	0.266 *** (0.066)	0.256 *** (0.067)	0.241 *** (0.070)
	(3) Tertiary or higher	−0.051 (0.039)	−0.060 † (0.035)	−0.073 * (0.035)	0.137 (0.093)	0.112 (0.096)	0.106 (0.096)
Income quintile [*Ref. (1) Poorest quintile (bottom 20%)*]	(2) Second quintile (20–40%)	−0.100 *** (0.025)	−0.109 *** (0.022)	−0.104 *** (0.024)	−0.017 (0.081)	−0.037 (0.080)	−0.024 (0.080)
	(3) Middle quintile (40–60%)	−0.084 ** (0.028)	−0.082 ** (0.028)	−0.082 ** (0.029)	−0.035 (0.081)	−0.036 (0.079)	−0.044 (0.080)
	(4) Fourth quintile (60–80%)	−0.099 *** (0.030)	−0.098 *** (0.029)	−0.098 *** (0.030)	−0.054 (0.076)	−0.059 (0.075)	−0.058 (0.074)
	(5) Richest quintile (top 20%)	−0.132 *** (0.030)	−0.133 *** (0.028)	−0.135 *** (0.029)	−0.047 (0.077)	−0.056 (0.077)	−0.051 (0.076)
Job situation: employee		0.024 (0.029)	0.032 (0.025)	0.041 (0.029)	0.048 (0.051)	0.043 (0.049)	0.058 (0.050)
Observations		1000	1000	1000	893	893	893
Pseudolikelihood		−344.78	−337.53	−347.68	−564.68	−554.98	−561.18
Wald χ^2 (d.f.)		61.01 (14)	70.94 (16)	50.68 (15)	24.26 (14)	32.92 (16)	29.77 (15)
R^2 McFadden		0.14	0.16	0.13	0.04	0.06	0.05
Akaike criterion (d.f.)		719.56 (15)	709.06 (17)	727.37 (16)	1159.37 (15)	1143.97 (17)	1154.36 (16)

Notes: Table 8 reports marginal effects from the *probit* models including GC. *d.f.* denotes degrees of freedom. Robust standard errors are shown in parentheses. † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9. DFI and subjective FV: marginal effects including GC.

		Difficulties in 30-Day Emergency Funds			Difficulties in 7-Day Emergency Funds		
		m1	m2	m3	m4	m5	m6
Making/receiving digital payments (including GC)		−0.583 *** (0.079)			−0.579 *** (0.087)		
Digital payments via Internet (including GC) [*Ref. (0) None*]	(1) One		0.015 (0.090)			−0.093 (0.091)	
	(2) Two		−0.066 (0.102)			−0.047 (0.113)	
	(3) Three		−0.123 (0.133)			−0.240 * (0.118)	

Table 9. *Cont.*

		Difficulties in 30-Day Emergency Funds			Difficulties in 7-Day Emergency Funds		
		m1	m2	m3	m4	m5	m6
Digital payments via mobile phone (including GC) [*Ref. (0) None*]	(1) One			0.093 (0.071)			0.063 (0.072)
	(2) Two			0.189 (0.149)			−0.047 (0.124)
Offline FI with credit card [*Ref. 0 Does not own*]	(1) Owns but not used	0.090 (0.067)	0.045 (0.067)	0.039 (0.067)	0.017 (0.071)	−0.014 (0.067)	−0.027 (0.068)
	(2) Owns and uses	0.049 (0.072)	0.005 (0.071)	−0.002 (0.071)	0.011 (0.074)	−0.014 (0.070)	−0.031 (0.070)
Gender: female		0.004 (0.042)	0.002 (0.043)	−0.010 (0.043)	0.029 (0.042)	0.032 (0.042)	0.029 (0.043)
Age		−0.008 (0.008)	−0.010 (0.008)	−0.010 (0.008)	0.005 (0.008)	0.003 (0.008)	0.003 (0.009)
Age squared		0.00007 (0.0001)	0.00007 (0.0001)	0.0001 (0.0001)	−0.0001 (0.0001)	−0.00005 (0.0001)	−0.00005 (0.0001)
Educational attainment [*Ref. (1) Primary or less*]	(2) Secondary	−0.135 † (0.073)	−0.117 (0.073)	−0.105 (0.074)	−0.072 (0.074)	−0.064 (0.071)	−0.058 (0.076)
	(3) Tertiary or higher	−0.139 † (0.072)	−0.113 (0.077)	−0.105 (0.078)	−0.081 (0.080)	−0.074 (0.081)	−0.068 (0.084)
Income quintile [*Ref. (1) Poorest quintile (bottom 20%)*]	(2) Second quintile (20–40%)	−0.024 (0.071)	−0.014 (0.073)	−0.025 (0.072)	−0.034 (0.072)	−0.046 (0.068)	−0.033 (0.072)
	(3) Middle quintile (40–60%)	−0.101 (0.064)	−0.094 (0.065)	−0.086 (0.066)	−0.018 (0.073)	−0.035 (0.070)	−0.009 (0.073)
	(4) Fourth quintile (60–80%)	−0.153 * (0.060)	−0.151 * (0.061)	−0.151 * (0.062)	−0.090 (0.066)	−0.104 † (0.063)	−0.085 (0.067)
	(5) Richest quintile (top 20%)	−0.137 * (0.064)	−0.143 * (0.064)	−0.147 * (0.064)	−0.096 (0.068)	−0.110 † (0.066)	−0.103 (0.068)
Job situation: employee		−0.058 (0.049)	−0.050 (0.049)	−0.056 (0.049)	0.002 (0.047)	0.004 (0.047)	0.009 (0.047)
Observations		893	893	893	893	893	893
Pseudolikelihood		−544.27	−547.33	−545.86	−549.80	−546.49	−552.58
Wald χ^2 (d.f.)		35.36 (14)	25.09 (16)	25.50 (15)	25.59 (14)	20.58 (16)	12.52 (15)
R^2 McFadden		0.05	0.04	0.04	0.02	0.03	0.02
Akaike criterion (d.f.)		1118.54 (15)	1128.67 (17)	1123.72 (16)	1129.61 (15)	1126.99 (17)	1137.17 (17)

Notes: Table 9 reports the marginal effects from the *probit* models including GC. *d.f.* denotes degrees of freedom. Robust standard errors are shown in parentheses. † $p < 0.10$, * $p < 0.05$, *** $p < 0.001$.

5. Conclusions

Digital finance is increasingly adopted by the population due to its advantages, including enhanced accessibility, reduced transaction costs for financial products and services, and greater opportunities for investment diversification (J. Liu et al., 2024). These benefits may contribute to higher disposable income, thereby facilitating savings and improving the management of financial hardships. Nevertheless, despite its potential advantages, digital financial inclusion (DFI) is not without risks related to individuals' financial vulnerability (FV), underscoring the importance of examining the contextual conditions under which DFI operates. In particular, digital shopping and payment environments may foster excessive or impulsive consumption behaviours, which can ultimately exacerbate FV (Qiu et al., 2025).

The relationship between DFI and FV has been examined empirically by a growing number of studies. However, the majority of this emerging research focuses on developing countries and overlooks relevant variables for capturing these phenomena, such as subjective measures of FV and indicators of offline financial inclusion (FI). This study contributes to the existing literature by extending the limited empirical evidence for economically advanced countries and by incorporating these additional dimensions into the analysis.

This paper examines whether DFI is associated with the FV of Spanish households, drawing on data from the 2021 *Global Findex Database* (GFD) compiled by the World Bank.

The findings reveal that individuals who engage in digital payments are significantly less likely to experience FV and tend to report fewer difficulties in accessing funds to cover unexpected expenses over short timeframes (30 or 7 days). However, this association becomes less evident when the analysis focuses on the specific digital channels (namely, the Internet or mobile devices). In particular, the percentage of individuals without emergency savings increases with the diversity of Internet-based payments conducted, rising from 45.37% among those who do not engage in digital payments to 51.39% among those performing all three types of operations considered. This evidence suggests that DFI is not necessarily associated with a stronger propensity toward precautionary saving.

These descriptive findings are supported by the marginal effects estimated using *probit* models. Individuals who have made or received digital payments exhibit a lower likelihood of experiencing FV, regardless of the specific FV indicator considered. In contrast, variables capturing the use of Internet and mobile devices for digital payments display more ambiguous associations with FV. While both channels are associated with a reduced probability of lacking financial resilience, greater diversity in Internet-based payments (that is, engagement in two or more types of transactions) reduces the probability of having emergency savings. This pattern does not hold for mobile-based payments, which maintain a positive association with emergency savings. Furthermore, when FV is assessed from a subjective perspective, both digital channels (i.e., Internet and mobile devices) appear to be primarily associated with greater perceived difficulties in accessing emergency funds.

This study provides evidence that DFI reduces an individual's FV in a developed economy such as Spain. To date, empirical evidence supporting this negative relationship has primarily been observed in emerging or developing economies, where financial inclusion remains substantially lower than in advanced economies (Demirgüç-Kunt et al., 2022). This negative relationship is likely attributable to the fact that DFI enables more efficient and cost-effective access to financial products compared to offline channels. However, DFI may also harm individuals' financial resilience, as the positive association between Internet-based payments and the lack of emergency savings suggests. Behavioural factors—such as impulsivity or a diminished perception of psychological loss (the "pain of paying") when using digital payment channels—may help explain this positive link between DFI and FV.

Our findings highlight the need to move beyond purely objective measures of FV by also incorporating its subjective dimension. Furthermore, it is important to include other variables, such as offline FI measures and indicators that capture the intensity of use of different tools for conducting online transactions. Neglecting the role of these factors may contribute to the persistence of mixed evidence in the academic literature and to the implementation of ineffective interventions, as policies could fail to address the underlying conditions that shape FV.

Regarding theoretical implications, this paper underscores the need to develop new frameworks that help to explain the process of financial decision-making through digital channels, especially in the context of economically developed countries. Such frameworks should aim to identify the underlying factors that account for the ever-decreasing reduction in FV as the use of certain digital channels increases.

As noted, our results indicate that while DFI generally reduces household FV, it can become counterproductive if pursued too intensively or through specific channels, such as the Internet. Accordingly, our practical recommendations focus on mitigating undesirable outcomes while reinforcing the role of DFI as a promoter of financial resilience.

First, initiatives aimed at enhancing DFI and ultimately reducing FV should be implemented alongside efforts to improve financial literacy, encourage the responsible use of technology, and establish regulatory frameworks that provide stronger protection for users of digital financial services. Such measures are critical not only to prevent factors—such as the diminished "pain of paying" and the increased accessibility of digital tools— from inadvertently promoting excessive or impulsive household consumption, but also to address the growing threat of digital fraud.

Second, online payment platforms (e.g., banking applications) should make the act of spending feel more tangible to users. For instance, when making online payments, animations could show money "leaving" a virtual wallet, or a progress bar could show the monthly budget decreasing. Additional confirmation messages could be displayed if spending exceeds previous patterns, and users could be given the option to set up alerts if their expenses surpass a specified amount or proportion of income.

Third, given the increasing frequency of fraud in a more digitalised financial landscape, robust fraud prevention strategies—such as advanced authentication protocols and consumer awareness programs—should be prioritized, as fraud can trigger impulsive spending that increases FV. And finally, public authorities could support the implementation of these measures by granting funding or by incorporating compliance with such initiatives as a condition for accessing subsidies.

This study has several methodological limitations that restrict the scope and reproducibility of its findings. First, the GFD primarily focuses on collecting information on FI, while providing comparatively limited data on economic and financial variables that could support the development of more comprehensive measures of FV. Second, the GFD lacks data on several variables identified in prior literature as determinants of FV. For instance, the absence of sociodemographic information—such as the presence of children or household composition—restricts the precise identification of FV drivers and limits the assessment of the actual role of DFI. This lack of variables may also contribute to the imperfect control of endogeneity, despite our efforts to implement the Gaussian Copula (GC) approach.

Third, the use of somewhat outdated cross-sectional data limits the ability to assess whether the relationship between DFI and FV persists over time within today's rapidly evolving economic environment. Although the GFD is collected every three years, we discarded the use of the most recent wave because key variables—such as the full set of Internet-based payment questions—are no longer available. These limitations prevent us from reproducing the measures required for this study and, therefore, from relying on the latest cross-section.

And fourth, although proportion of omitted observations is relatively low, the application of simple imputation techniques may introduce bias by distorting variables distributions and potentially underestimating or overestimating their variances.

To address these limitations, future research could develop a specific survey designed to collect comprehensive information on FV, encompassing a broader array of economic, financial, sociodemographic and behavioural variables. Such a survey should include detailed questions regarding household composition, the presence of dependents, income sources, and access to financial tools, as well as indicators of financial stress and resilience. Administering this survey in successive waves would provide time-consistent data, enabling longitudinal analyses to investigate causal relationships between DFI and FV. In parallel, comparing results obtained using more sophisticated multiple imputation techniques, and extending the analysis to other economically developed countries, would further enhance the robustness of the conclusions.

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Data Availability Statement: The data used in this study were obtained from the 2021 wave of the Global Findex Database, a comprehensive dataset compiled by the World Bank. These data are publicly available to any researcher at: https://data360.worldbank.org/en/dataset/WB_FINDEX (accessed on 10 September 2025).

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Notes

1. Access to formal financial products, even when provided through offline channels, may be perceived as progress towards digitalisation in the context of less developed countries or those with nascent digital infrastructures. This interpretation is evident in the study by Xu et al. (2024), where access to credit cards is incorporated as a component of the DFI index. By contrast, research focusing on more developed economies, such as Norway (Seldal & Nyhus, 2022), excludes credit cards from the DFI construct, which is more narrowly defined in relation to digital tools and digital-only payment methods.
2. As defined, the variable *lacking financial resilience* is the opposite of that proposed by Verma and Chatterjee (2025).
3. The GFD also includes information on bank account ownership. However, these data are not available for Spain or for most developed economies.

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