Information preference in equity crowdfunding investment: the moderation of financial knowledge and digital agency

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Abstract

Legitimacy, speed and breadth of digital information disclosed through equity crowdfunding (ECF) platforms set the relevance of understanding the behaviours of not-professional not-skilled investors when they decide to finance a startup, typically high-risk business. This issue is reinforced by the fact that herding behaviour of ECF investors is an established way by which they tend to fill their gaps in knowledge, skills, and experience. We administered a Discrete Choice Experiment to a sample of N=1,018 Italian household heads representative of the Italian consumers and retail investors. We analyse their preferences toward different types of information affecting their decision-making, allegedly guiding their herding behaviour. As expected, we find that these individuals are influenced more significantly by public information sources (the percentage of equity already paid by other investors and the number of social networks managed by the startup) and less by private ones (the number of professional investors and the pre-money evaluation of the startup). Moreover, we uncover a moderation role of financial knowledge and digital agency. In fact, individuals with higher levels of financial literacy upscale the perceived importance of presence of financial professionals. The upscale is even higher for individuals showing high levels of digital agency. This evidence is further proof of the importance of programs, both institutional and private, aimed at increasing the levels of financial education and digital agency in a country.

JEL: G11; G14; G23; G24

Key words: Equity crowdfunding; private/public information; herding behaviour; Discrete Choice Experiment; financial knowledge; digital agency; financial commitment.

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1. Introduction

The digitalization of finance implies transformations in both the demand side of capital and the supply side. Fintech solutions, an expression of these transformations, accelerate financial disintermediation with the development of digital venues through which capital may flow. Equity crowdfunding (ECF) is an example of these venues, and it developed because particularly fitting to a type of capital seekers, toward whom the greatest fear of adverse selection by classical lenders (the banks, the stock exchanges) is concentrated.

[1] The ideas and positions in the paper are personal views of the authors and cannot be attributable to Consob.

However, digital solutions do not eliminate the real issue of capital exchange, which lies in the intensity and forms of risk transferred from the demand to the supply of side of capital markets. The classical paradigms of finance pose the issue of how information should unambiguously convey the risk transferred from borrowers to lenders, that is, from financed entrepreneurs to investors. This riskiness results at highest levels in startups by their nature, with reduced (or absent) track records and focus on innovative businesses.

This increased riskiness, paradoxically, cannot be assumed to be matched by a corresponding (and desirable) increased risk-bearing capacity on the part of investors. In the case of ECF, in fact, the nature of the investment, which is generally small in amount and highly accessible thanks precisely to digitalization, identifies the type of investor with the expression 'crowd,' i.e., investor of modest size, not characterized by marked financial or economic expertise in general. The very expression 'crowd-funding' would seem to emphasize the characterizing element of the operation, that is, the financing offered by the ‘crowd’, as opposed logically to what ‘professional financing’ might be.

Thus, in the context of ECF, the democratization of access to capital has introduced a novel dimension to investment decisions, allowing, on the one hand, startups and small businesses to raise funds from a diverse pool of investors. On the other hand, investors now have direct access to a diverse range of entrepreneurial ventures, bypassing traditional intermediaries. This paradigm shift necessitates an exploration of how retail investors navigate this new information environment to inform their investment decisions (Hornuf and Schwienbacher, 2018). It follows that the 'financial contract' signed in ECF transactions takes place in a condition of paradox: maximum riskiness, on the demand side of capital; minimum experience/ expertise/ professionalism on the supply side of capital.

The solution of this paradox is the legitimacy, speed and breath of the *information* that is conveyed from bid and offer of the financial market, allowed by digitalization.

In this paper we explore preferences of individuals toward different types of information affecting their decision-making, precisely, on the one hand, items of public information (the percentage of equity already paid by other investors, the number of social networks managed by the startup, and the number of retail investors already intervened in the campaign), and on the other hand, proxy of private sources (the analysts’ pre-money evaluation of the startup and the presence of professional investors). Moreover, we investigate if these preferences are affected by levels of financial and digital knowledge of individuals. To this end, we administered a Discrete Choice Experiment to a sample of N=1,018 Italian household heads representative of the Italian consumers and retail investors.

The structure of the paper is as follows. In section 2, the theoretical background delves into the economic value of information, with a specific focus on how information is perceived and valued by retail investors, its role in shaping investment preferences, and the distinction between private and public information. In section 3, we develop the conceptual model of the research and in section 4 the methodology adopted. In section 5, we describe the sample and the main summary statistics of the dataset. Section 6 presents the results of the model estimates. Finally, section 7 and 8 discuss the main findings and concludes the paper.

2. Theoretical background in retail investment decision-making process

2.1. Economic value of information: private vs public information

The economic landscape has undergone significant transformations in recent years, driven by the increasing importance of information in decision-making processes and by an increasing velocity in information sharing thanks to the digital ecosystem (Thakor, 2020). Information is recognized as a critical asset that can influence economic activities and outcomes, particularly in the realm of investment and financing, where adverse selection and risk are around the corner. Adverse selection refers to the presence of information asymmetry, where one party possesses more information than the other, leading to potential market distortions (Cassar, 2004), and eventually to the financing of less promising ventures (Akerlof, 1970; Carpenter and Petersen, 2002). Managing and mitigating risks, both systematic and idiosyncratic, is fundamental for sustaining a stable and resilient financial environment. This is especially true for alternative financial markets based on FinTech and digital innovations (Blaseg et al., 2021).

Retail investors, comprising individual agents who commonly possess fewer investing experience and capabilities compared to institutional and professional investors, play a significant role in innovative financial markets such as the ECF. Previous research proved that retail investors followed different decision-making dynamics compared to professional investors (Vismara, 2019). Indeed, their investment decisions are influenced by a diverse range of information, including news, analyst reports, entrepreneurs' behaviour, behaviour of the crowd of investors and social media sentiment, and in other words by a community logic. Professional investors, instead, are driven by a market logic (Vismara, 2019). Moreover, ECF is based on a FinTech ecosystem, where information flows rapidly and publicly across a digital landscape (Goldfarb & Tucker, 2019).

Understanding the types of information that retail investors evaluate to pick the most promising ECF projects is crucial to understanding their financing decisions. Contrary to professional investors, retail investors often rely on information that is easily accessible, understandable, and aligns with their investment goals and risk tolerance (Hsee, 1998). In other words, decision-makers facing a high variety and complexity of information tend to evaluate more heavily those characteristics that are more easily understood following the so-called "evaluability heuristic" and "less-is-better effect". Indeed, behavioral finance theories posit that investor decisions are not purely rational but are influenced by psychological factors (Baltussen, 2009).

Moreover, retail investors, especially those lacking specialized experience/knowledge, are known to be prone to a range of cognitive distortions (Kahneman and Tversky, 1974, Baltussen, 2009) and limited rationality (Camerer, 1998) prone to fallacious evaluations (Ahlers et al., 2015; Hornuf and Schwienbacher, 2014). Therefore, they are inclined to alleviate the complexity of their decisions through the use of thinking shortcuts (heuristics) in order to reach satisfactory solutions (Simon, 1955). The decision to invest, or not, precisely because of the modest scale of financial investment in ECFs, makes it plausible that it is purely individual and hardly assisted by outside advisors. Retail investors, left to decide on their own, lacking sufficient skills and experience to assess the investment prospect, run into high monitoring costs (Ahlers et al., 2015; Cumming et al., 2019); they therefore implement practical methods, even traceable to heuristic procedures, to improve their choice process under conditions of information asymmetry and limited rationality, trying to acquire as much information as possible, both technical-financial and by following the behavior of economic agents they assume to possess private and broader information sets. This phenomenon is often referred to as the "*herding effect*" (Scharfstein and Stein, 1990) and describes the tendency of individuals to mimic the behavior of a group, gaining an economic advantage from the aggregation of individual pieces of information learned from others (Grossman and Stiglitz, 1976) by aligning their own choices and beliefs with those of operators deemed more informed, or at least with those of a group they belong to (Bikhchandani et al., 2001). This trait of retail investment decision-making process is therefore particularly relevant for ECF investors.

2.2.Dissemination of digital information in financial markets

The advent of digital technologies has revolutionized the spectrum of technologies that empower investors with real-time information and analytical capabilities.

The ability of an individual to control and adapt to a digital world is defined as *digital agency* (Passey et al., 2018, p. 426). It is a broader concept that comprehends the capacity of engaging with technology in a 'meaningful' and 'capital enhancing' way (Pearce and Rice 2017; Siddiq et al., 2023).

Digital agency, encompassing digital competence, digital confidence, and digital accountability, plays a pivotal role in shaping the investment decisions of retail participants (Passey et al., 2018). Digital competence involves the ability to comprehend and utilize digital information safely and effectively, embracing both digital skills and literacy.

Concurrently, digital confidence refers to the adeptness in utilizing digital tools and, in particular, confidence in applying digital competence in everyday situations. In other words, it reflects the ability to use digital tools, such as internet and other applications or software, autonomously, expertly and in different contexts. For financial decision-making, retail investors who demonstrate digital confidence and digital savvy behaviors leverage technological resources to assess risks, explore investment opportunities, evaluate different sources of information and engage with the dynamic crowdfunding ecosystem.

Digital accountability involves the responsible and conscious behaviour in the digital world. In the ECF context it reflects the use of digital information and platforms, ensuring ethical and transparent investment practices in the digital realm.

2.3. Hard vs soft information in ECF

In this study, we draw also upon the theoretical framework that categorize information into hard and soft (Petersen, 2004; Liberti and Petersen, 2018). Hard information pertains to verifiable facts with widespread consensus, typically resistant to alteration during the investment period. Conversely, soft information is dynamic, changeable and susceptible to diverse interpretations and challenges in verification (Bertomeu & Marinovic, 2016; Liberti & Petersen, 2018).

In the realm of ECF, digital platforms present a transformative opportunity by potentially mitigating the transaction costs associated with acquiring, disseminating, and interpreting information, including soft information (Goldfarb & Tucker, 2019). Indeed, the architecture of ECF platforms, characterized by open access, encourages entrepreneurs to disclose a wealth of information, fostering an environment where hard facts and high-quality soft information are shared at scale. Additionally, the informational landscape in ECF is subject to constant updates, revisions, and reinterpretations, emphasizing the fluidity of the latter. This democratized information flow benefits both entrepreneurs and investors, allowing for a more informed decision-making process (Estrin et al., 2021).

3. Conceptual model

In our framework we remember that financing offered by the 'crowd' is opposed logically to what 'professional financing' might be, implying that investors hold minimum experience/ expertise/ professionalism. As anticipate in previous sections, in financial markets, information is often classified dichotomously into private and public information. Private information refers to data known to a select few, introducing information asymmetry and providing a competitive advantage to those who possess it. Public information, on the other hand, is widely available and known to all market participants, depending on how quickly it is disseminated (Morris and Shin, 2002). In the ECF context, public information is disseminated through crowdfunding platforms and other accessible channels, e.g. social media. The efficient selection of promising investments relies on the assimilation and interpretation of both private and public information, reflecting also the aggregate knowledge of market participants. Moreover, information that could be exploited in the ECF investment decision making process may also be distinguished between hard and soft information.

Keeping in mind that investors in ECF are more likely to make a decision through herding available information (i.e. public information), constructing a knowledge that is called the 'wisdom of the crowd' (Polzin et al., 2017), and also soft information (Estrin et al., 2021), we can formulate the first hypothesis of the paper:

H1: *Economic value and the nature of the information source determine the investment preferences of retail investors.*

> **H1a:** *Retail investors tend to consult sources of information that are public rather than private ones.*
>
> **H1b:** *Retail investors tend to consult sources of information that are soft rather than hard ones.*

We know from literature (Weick, 1995) that *financial knowledge* is a key element in the process of information evaluation by retail investors, with a profound impact on their ability to discern, interpret and act on financial and non-financial information. Financially literate retail investors are better equipped to critically evaluate information sources and assess their credibility and relevance, thus discerning the signal from the noise. A higher level of financial knowledge enables them to make well-informed investment decisions and navigate complex financial terrain with confidence (Yang et al., 2023; van Rooij et al., 2011). Therefore we argue the role of moderation played by financial knowledge, proven by the tendency of skilled retail investors to consider with more attention the sources of private information. This implies the second hypothesis of this paper:

> **H2:** *Retail investors with high financial knowledge tend to consult sources of private information.*

The speed at which information circulates in the digital age has profound implications for retail investors participating in ECF. The velocity of information dissemination is accelerated by online platforms, social media, and digital communication channels, creating an environment where news and real-time updates swiftly reach a wide audience. This rapid dissemination has a direct impact on investors' decision who are appointed to rapidly incorporate new information in their decision-making processes. Quick access to information means that retail investors must adeptly process and incorporate new developments into their investment decisions in real-time. This brings about the third hypothesis of this paper:

> **H3:** *Retail investors with high digital agency tend to consult sources of private information.*

To test our conceptual framework (Figure 1) we exploit the case of Italian ECF marketplace which can be considered significantly developed, in terms of business (1,325 fundraising campaigns launched, of which 81.4% closed successfully, and 571,680,000 € of capital raised; Politecnico di Milano, 2023), regulations (in 2013 Italy became the first country in Europe to have a specific discipline on crowdfunding; CONSOB regulation 18592/2013) and ECF platforms (48 authorized platforms by the CONSOB; Politecnico di Milano, 2023).

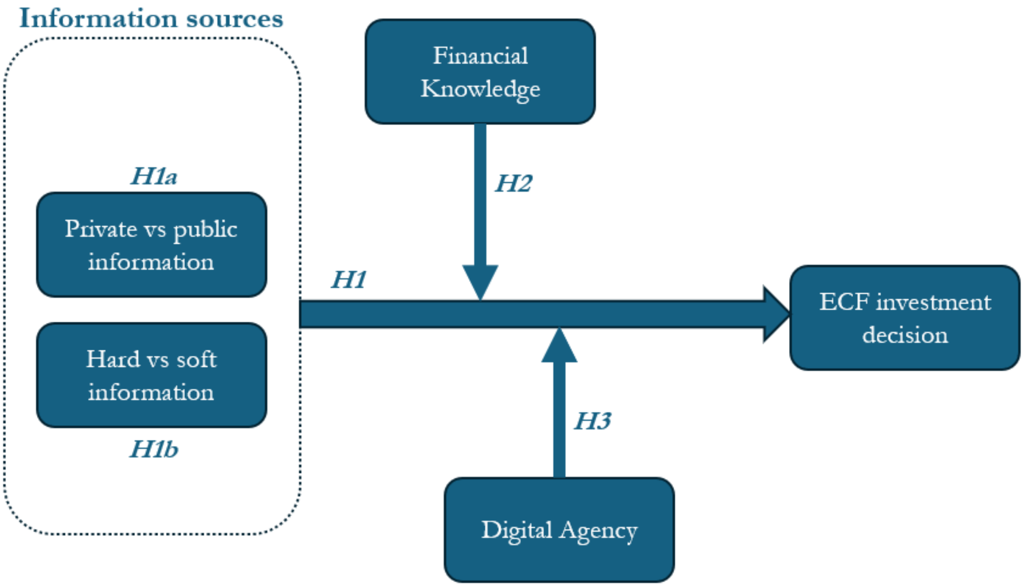

Figure 1 conceptual model

4. Methodology

4.1. The Discrete Choice Experiment (DCE)

Discrete Choice Experiments constitute a quantitative research method useful for estimating individuals' subjective preferences and understanding the factors that influence their decision making (Train 2003). A DCE is based on an indirect method of preference detection in that individuals are not required to provide an absolute measure of the utility associated with a choice, but rather to express a preference among hypothetical alternatives through a series of choice scenarios (Ali and Ronaldson, 2012). Methodologically, a choice experiment requires defining the *attributes* that can influence preferences, the *levels* for each attribute, and the *choice scenarios* (choice set).

4.2.Attributes of the experiment

The *attributes* of the choice alternatives elicited in this paper reconcile the conceptual frame of the paper with the information effectively available on the web campaigns presented by the Italian ECF platforms, to be representative of the different sources of information that a potential retail investor may consult. This also reflects the legitimacy of the information available and requested by the platforms. As a results, the attributes considered are as follows:

- percentage of company share distributed to future members (investors/shareholders) in case of achievement of the raising campaign (%EQUITY-OFFERED);[2]
- presence of a link to an active social profile of the startup on Facebook/ Instagram/ Twitter (X)/ LinkedIn (SOCIALS);
- pre-money value in Euros of the startup estimated by analysts and advisors prior to launching the equity crowdfunding campaign ($PRE-MONEY);
- percentage of investment confirmed (paid) by investors (%INVEST-CONFIRMED);
- number of professional investors present, such as business angels, venture capital, financial intermediaries (N-PROF-INVESTORS);
- number of retail investors present (N-RET-INVESTORS).

Therefore, as shown in Table 1, we connect these six attributes, arising from the real-world of the Italian ECF platforms, with their plausible nature of private/public information, on the one hand, and of hard/soft information, on the other hand.

Table 1 Empirical attributes and conceptual frame

		Economic value of the information	
		Public	**Private**
Nature	**Hard information**	SOCIALS	% EQUITY-OFFERED $PRE-MONEY
	Soft Information	%INVEST-CONFIRM N-RET-INVESTORS	N-PROF-INVESTORS

4.3.Levels of attributes

Then, the definition of the *levels*, similarly to the elicitation of the attributes, was based on empirical evidence emerging from the web campaigns, to represent plausible investment choices consistent with the Italian market (Coast et al., 2007). Coherently, a data collection using web scraping techniques was conducted on the main Italian platforms, selecting those with values above the fiftieth percentile for number of campaigns published and amount of capital raised. From the ten Italian platforms identified, we excluded those operating exclusively in the real estate sector (i.e., Concrete Investing, Walliance). Therefore, we analyzed eight platforms: 200Crowd, Backtowork24, CrowdFundMe, Doorway, MamaCrowd, Opstart, StarsUp, WeAreStarting.

A series of web scraping and data mining algorithms then extracted attribute reference information for each campaign. For each attribute, from the statistics of the platforms consulted, we identified three levels (i.e. minimum, median, and maximum), excluding outliers. Each attribute was then defined by dummy coding with three levels, with the exception of social media.. The latter attribute we created a categorical variable, related to the number of social media visible in web campaigns (zero, two or four socials).

[2] Equity offered is the complementary to 1 of equity retention.

The number of attributes and levels of each attribute is not random and results from a trade-off between the information obtainable from the experiment and the cognitive load required of participants (Mangham et al., 2009; Johnson et al., 2013). These, in fact, influence the number of choices participants are subjected to according to the formula:

$$(1)\ cs = l - k + 1$$

where l is the number of levels and k is the number of attributes. Therefore, with 19 total levels and six attributes, the expected number of choice scenarios is 14. Table 2 provides a summary of the levels by attribute considered in our DCE.

Table 2 Levels of the DCE by attribute

Attribute	*Levels*
% EQUITY-OFFERED	2% 9% 85%
SOCIALS	Nessuno (Facebook + Instagram) (Twitter (X) + LinkedIn) (Facebook + Instagram + Twitter (X) + Linkedin)
$PRE-MONEY	1,000€ 10,000€ 2,000,000€
%INVEST-CONFIRM	0% 88% 100%
N-PROF-INVESTORS	0 1 5
N-RET-INVESTORS	16 122 355

4.4. The choice sets of the experiment

Each choice set consists of two choice alternatives and one no-choice option, obtained by combining the attribute levels. From this process, the experimental design of a DCE is obtained, resulting in a matrix of values where in the columns are located the attribute levels and in the rows the choice alternatives (Huber & Zwerina, 1996). In this study, we opted for the generation of a D-efficient experimental design obtained using a specific program developed in the R language: idefix (Traets et al., 2020). The program, based on the inputs provided following the DCE design and relying on the CEA algorithm (Pérez-Troncoso, 2020), generated a design matrix containing fourteen choice sets.

Additionally, the obtained experimental design matrix must then be interpreted and decoded in order to associate the values of the levels of each attribute with the choice alternatives and obtain the choice sets. This step was also developed in the R language with a special function in the idefix package. The alternatives obtained from the generation of choice sets, therefore, present optimal combinations of attributes and levels that represent purely hypothetical investment solutions and may not necessarily have economic significance. In fact, the key to the interpretation of a DCE does not lie in the actual choice of a specific alternative, but rather in how the choice is oriented according to the presence of certain levels of the attributes. For this reason, alternatives, having no specific parameters (alternative-specific), are “unlabeled” and referred to rather as “alternative A” or “alternative B”.

Although observing the sequence of the 14 choice sets it may happen that certain levels are repeated more frequently than others, usually an efficient experimental design possesses the property of balancing attributes and levels (Szinay et al., 2021). However, attempting to seek a perfect balancing between attributes and levels, and constraining it, may result into sub-optimal designs. Therefore, it was decided not to impose this additional constraint in order not to force the optimization proposed by the generative algorithm.

Finally, in order to guide the participants' choices, we provide the context of the ECF investments, as these are innovative startups requesting financial capital by equity crowdfunding, starting with a share capital of €10,000, based in Italy and operating in the digital and technology (high-tech) sector.

4.5.The on line survey

The choice experiment is presented in the form of an online survey, through which sociodemographic information about the participants is also collected, a set of questions on financial literacy and attitudes toward digitization. To reduce the cognitive overload of participation in the choice exercise and thus minimize possible response bias, three techniques were adopted.

First, two alternatives within the same choice scenario were allowed to have some attributes with the same level (attribute level overlap) in order to focus participants' attention on certain attributes, reducing the complexity of their task and improving the effectiveness of the experiment (Jonker et al., 2018).

The second technique involved the use of colours to highlight differences in levels between alternatives. Specifically, a scale of purple and grey was adopted to highlight the maximum (dark purple) and minimum (light grey) levels within the same attribute (Jonker et al., 2018). The colour choice is guided by the fact that these are colours that can be distinguished even by subjects with colour blindness Figure 2.

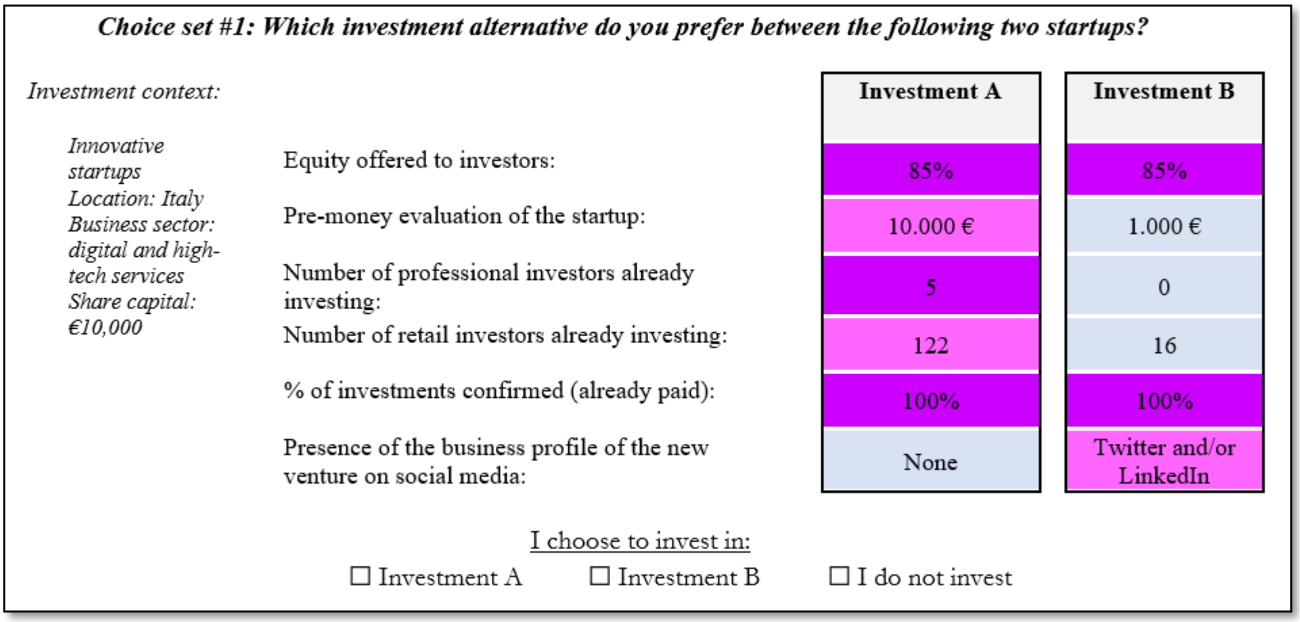

Figure 2 Graphical representation of a choice set

Finally, the 14 choice sets, resulting from the experimental design, were divided into two blocks of seven each (blocking), which were alternately and randomly submitted to participants. Each participant then, once randomly assigned to one of the two sub-samples (leg 1 or 2), underwent the final survey where seven choice scenarios were provided instead of 14.

4.6.Model specification

The *Conditional Logit* (McFadden, 1974) is one of the first models developed to analyze discrete choices. It is based on the assumption that individual preferences are constant across alternatives and that the only variations are due to differences in the characteristics of the alternatives themselves. The probability that an individual will choose alternative j among J possible alternatives is modeled through the expression:

$$(2)\ \Pr(choice = j) = \frac{\exp{(V_{ij})}}{\sum_{j=1}^{J} \exp{(V_{ij})}} \quad ,$$

where Vij represents the estimated utility for alternative j by individual i, and the denominator the sum of estimated utilities for all alternatives.

5. The sample

Preliminary, we conducted an online pilot test via Google Forms during the period of October 2022 to assess participants' understanding of the tasks and interface, as well as to identify any technical problems or ambiguities in the questions. At the end of the pilot test, a short questionnaire was administered to participants to collect comments or suggestions on the clarity of the tasks assigned in the survey. The data collected at this stage were examined to assess the distribution of responses and the effectiveness of the selected questions. Descriptive statistics were calculated for the choices made by the participants and any discrepancies or anomalies in the data were examined.

The final sampling and the administration of the full experiment were conducted in the period of December 2022 - January 2023 by the market analysis company GfK Italia. The target population sampled includes Italian household heads and represents the Italian consumer and retail investor panel. It is important to note that the sampled subjects were not necessarily required to know about equity crowdfunding or have had previous investment experience, so as not to bias the sample by making it subject to survivorship bias.

The administration of the survey and experiment was conducted by GfK, which provided its own digital space on which to host the survey and invite participants to complete the experiment for a reward (reward).

The final sample of individuals surveyed is N=1.018, which exceeds the minimum threshold needed to estimate an ECD (Johnson and Orme, 1996):

$$(3) \qquad n \geq 500c/ta$$

Where n is the number of participants, t the number of choice sets, a the number of alternatives per choice set (excluding the status quo option), and c the maximum number of levels per single attribute.

Table 3 presents the characteristics of the sample population and offers a nuanced understanding of the demographic and socio-economic composition of the study participants. The dataset includes information from 1018 individuals, providing insights into their age distribution, gender composition, geographical location, town size, educational background, and professional roles. The mean age of the participants is 52.47 years, with a standard deviation of 11.24, ranging from 22 to 75 years. The gender distribution indicates that 79.5% of the participants are male, while 20.5% are female. Geographically, the majority of participants are from the South and islands region (36.1%) of Italy, followed by the Northwest (34%), Center (14.6%), and Northeast (15.3%). Town size diversity is represented, ranging from less than 5000 residents (14.2%) to over 500,000 residents (12.2%). Educational backgrounds vary, with the majority having a high school diploma (45.9%) and a significant proportion holding a university degree (32%). Professional roles encompass a wide range, including office workers or servicepersons (31.1%), retirees (18.3%), and individuals identifying as students (1%).

Table 3 Socio-demographic descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	1018	52.466	11.238	22	75
Gender composition	.	.	.	.	.
Male	1018	.795	.404	0	1
Female	1018	.205	.404	0	1
Geographical location	.	.	.	.	.
North west	1018	.34	.474	0	1
North east	1018	.153	.36	0	1
Center	1018	.146	.354	0	1
South and islands	1018	.361	.48	0	1
Town size	.	.	.	.	.
< 5000	1018	.142	.35	0	1
5000-10000	1018	.108	.311	0	1
10000-30000	1018	.27	.444	0	1
30000-100000	1018	.231	.422	0	1
100000-500000	1018	.127	.333	0	1
>500000	1018	.122	.327	0	1
Educational background	.	.	.	.	.
No education	1018	.001	.031	0	1
Primary school with diploma	1018	.004	.063	0	1
Middle school without diploma	1018	.001	.031	0	1
Middle school with diploma	1018	.105	.307	0	1
High school without diploma	1018	.032	.177	0	1
High school diploma	1018	.459	.499	0	1
University without degree	1018	.078	.268	0	1
University degree	1018	.32	.467	0	1
Professional roles	.	.	.	.	.
Student	1018	.01	.099	0	1
Homemaker	1018	.02	.139	0	1
Retired	1018	.183	.387	0	1
Looking for first job	1018	.012	.108	0	1
Looking for job	1018	.028	.164	0	1
Executive	1018	.015	.121	0	1
Middle manager	1018	.06	.237	0	1
Office worker or serviceperson	1018	.311	.463	0	1
Teacher	1018	.044	.206	0	1
Worker shop assistant employed farmer or apprentice	1018	.189	.391	0	1
Entrepreneur	1018	.021	.142	0	1
Freelancer with employees	1018	.005	.07	0	1
Freelancer with no	1018	.058	.234	0	1

employees					
Trader farmer craftsman with employees	1018	.015	.121	0	1
Trader farmer craftsman without employees	1018	.014	.117	0	1
Helper employee	1018	.004	.063	0	1
Others	1018	.014	.117	0	1

5.1.Summary statistics

In addition to the choice experiment attribute variables, moderation variables measuring the participants' level of financial knowledge and digital agency were included (**Table 4**).

In this study, we operationalize financial knowledge using the "Big Five" questions developed by Lusardi and Mitchell (2014), where participants are assigned a score ranging from 0 to 5 based on their responses. Additionally, we introduce a dichotomous variable, termed "Dummy financial knowledge", which takes on a value of 1 if an individual scores above or equal to the median on the Big Five questions, and 0 otherwise. Turning to digital competence, this construct is measured through questions adapted from the OECD (2022), resulting in scores ranging from 0 to 7. Digital savvy behavior, an essential aspect of digital agency, is gauged through questions inspired by the OECD (2022), yielding scores within the range of 0 to 7. Digital confidence is assessed by questions pertaining to digital and internet usage, also drawn from the OECD (2022), with scores ranging from 0 to 15. We then derive a comprehensive measure termed "Digital agency" as the weighted mean of scores obtained on digital competence, digital savvy behavior, and digital confidence, with values ranging from 0 to 1. To further categorize individuals, a dichotomous variable, "Dummy digital agency," is introduced, taking on a value of 1 if an individual's Digital Agency score is above or equal to the median, and 0 otherwise.

***Table 4** Moderating variables description*

Variable	*Description*	*Values*
Financial knowledge	Score obtained on "Big Five" questions on financial knowledge (Lusardi and Mitchell, 2014)	0-5
Dummy financial knowledge	A dichotomous variable =1 if the individual scored above or equal to the median on the Big Five questions on financial knowledge; =0 otherwise	0;1
Digital competence	Score obtained on questions relating digital competence and skills adapted from (OECD, 2022)	0-7
Digital savvy behaviour	Score obtained on questions relating digital savvy behaviour and accountability adapted from (OECD, 2022)	0-7
Digital confidence	Score obtained on questions relating digital and internet usage adapted from (OECD, 2022)	0-15
Digital agency	Weighted mean of the scores obtained on digital competence, digital savvy behaviour and digital confidence.	0-1
Dummy digital agency	A dichotomous variable =1 for values of the Digital Agency above or equal to the median; =0 otherwise	0;1

Table 5 summarizes key statistics related to financial knowledge and digital agency among the 1018 participants in our study. For financial knowledge, participants scored an average of 3.147 out of 5, with a standard deviation of 1.780, indicating moderate variability in scores. The distribution is skewed (-0.471) and exhibits positive kurtosis (1.804). The t-value of 56.401 is highly significant, suggesting a substantial difference in financial knowledge scores. The corresponding dummy variable for financial knowledge indicates that approximately 63.8% of participants scored above or equal to the median, with a standard deviation of 0.481 and a significant t-value of 42.293. Turning to digital competencies, participants scored an average of 3.682 out of 7, displaying moderate variability (SD = 2.059). Digital savvy behavior and confidence also reveal noteworthy statistics, with average scores of 4.775 and 4.674, respectively. The digital agency, representing the combined effect of digital competence, savvy behaviour and confidence, exhibits an average score of 0.507, suggesting a moderate level of engagement and providing insights into participants' capabilities in these domains. The DV for digital agency shows that, on average, 51.1% of participants score above the median.

Table 5: summary statistics of moderating variables

	N	Mean	SD	Min	Max	p25	Median	p75	Skewness	Kurtosis	t-value
Financial knowledge	1018	3.147	1.780	0	5	2	4	5	-.471	1.804	56.401
DV fin. knowledge	1018	.638	0.481	0	1	0	1	1	-.572	1.327	42.293
Digital competence	1018	3.682	2.059	0	7	2	4	5	-.448	2.126	57.043
Digital savvy behav.	1018	4.775	2.082	0	7	4	5	7	-.76	2.607	73.184
Digital confidence	1018	4.674	3.506	0	15	1	4	7	.698	2.757	42.53
Digital agency	1018	.507	0.210	0	1	.371	.54	.66	-.472	2.677	76.971
DV digital agency	1018	.511	0.500	0	1	0	1	1	-.043	1.002	32.587

Moreover, individuals with a low financial knowledge (369) presented an average age of 49.9, with a standard deviation of 10.929. The gender distribution in this sub-group indicates that approximately 21.4% are female. In contrast, the sub-group of those with a high financial knowledge score of 1 consisted of elder individuals (649) with an average age is 53.9 and a standard deviation of 11.165. The gender distribution in this sub-group indicates that approximately 20% are female.

The difference in mean ages between the sub-group of low financial knowledge and the sub-group of high financial knowledge is -3.97 (SD=0.72) years and significant (Two-sample t-test), indicating that, on average, individuals with a higher financial knowledge score are elder than those with a lower financial knowledge.

Furthermore, individuals with a low digital agency (498) presented an average age of 52.2, with a standard deviation of 11.626, ranging from 22 to 75 years. The gender distribution in this sub-group indicates that approximately 18.9% are females. The sub-group of individuals with a high digital agency consists of 520 participants, with an average age of 52.7 and a standard deviation of 10.859. The gender distribution in this sub-group indicates that approximately 22.1% are females. However, the t-test results suggest that there is no significant difference in mean scores between the sub-groups of low digital agency and high digital agency.

Table 6 show that the correlation coefficient between financial knowledge and digital agency is 0.398.

Table 6 Pairwise correlations FK - DA

Variables	(1)	(2)
(1) Financial Knowledge	1.000	
(2) Digital agency	0.398*	1.000

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

6. Results

6.1. Full model

We first estimate the impact of the attributes' levels on the willingness-to-invest of retail investors with a conditional logit model. The results from the regression are reported in Table 7. Starting with the equity offered attribute, we find that retail investors tend to prefer fundraising campaigns that offer a higher equity share to the crowd (85%) than a campaign in which entrepreneurs retain most of the shares for themselves (2%), with a highly significant coefficient (P-value < 0.01) of -0.266. Considering the new venture's pre-money valuation, investors showed a weakly significant preference for higher valuations (2,000,000 €) than small companies valued at €1,000 by analysts before the fundraising campaign was launched. Focusing on the other attributes, individuals showed a significantly strong willingness to invest in alternatives in which a large number of professional investors (at least 5) had already invested. Similarly, campaigns in which more crowd-investors (355; or at least 122) bid are a strong incentive to invest. Analysing the crowd financial commitment, retail investors tend to strongly and significantly increase their willingness-to-invest for campaigns where at least 88% (but preferably 100%) of bids are confirmed. Regarding the new venture's social media accounts, retail investors tend to interpret the absence of social media as a strong and significant negative signal, but they also tend to prefer as large a social media presence as possible (four active profiles: Facebook, Instagram, Twitter (X) and LinkedIn).

We controlled also for the status-quo, that is the no-choice alternative, which presents a significant negative coefficient of -0.620 (p < 0.001) and suggests a significant propensity to choose one of the investment alternatives in each choice set.

Table 7: baseline estimation model

		(1) Full model Coef./(Std. err.)
	Y=choice	
	Status-quo	-0.620***
		(0.08)
% EQUITY-OFFERED	2% offered	-0.266***
		(0.06)
	9% offered	-0.002
		(0.05)
$PRE-MONEY	1.000€ premoney	-0.100*
		(0.06)
	10.000€ premoney	0.057
		(0.06)
N-PROF-INVESTORS	0 professional investors	-0.307***
		(0.05)
	1 professional investors	-0.143***
		(0.05)
N-RET-INVESTORS	16 retail investors	-0.275***
		(0.05)
	122 retail investors	-0.057
		(0.06)
%INVEST-CONFIRM	0% confirmed	-0.713***
		(0.05)
	88% confirmed	-0.049
		(0.05)

SOCIALS	None	-0.384***
		(0.05)
	Twitter (X) and/or LinkedIn	-0.239***
		(0.06)
	Facebook and/or Instagram	-0.156**
		(0.06)
	N	1018
	Pseudo R-squared	0.04
	AIC	14999.32
	BIC	15110.90

Reference class for attribute 1 (Equity offered) is: 85%
Reference class for attribute 2 (Premoney) is: 2.000.000€
Reference class for attribute 3 (Professional investors) is: 5 professional investors
Reference class for attribute 4 (Retail investors) is: 355 retail investors
Reference class for attribute 5 (Bids confirmed) is: 100%
Reference class for attribute 6 (Social media) is: Facebook, Instagram, Twitter (X) and LinkedIn
* $p<0.10$, ** $p<0.05$, *** $p<0.010$

We then employed a series of stepwise backward regressions to understand the relative importance of each attribute. The loss of information caused by the sequential elimination of one attribute at a time provide insights about the relative attribute importance. The estimation results from the six additional reduced models as well as the models' fit statistics and information criteria are reported in Table 8.

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Table 8: attribute importance – stepwise backward elimination models

		(1) Full model Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status-quo	-0.620***	-0.579***	-0.648***	-0.530***	-0.573***	-0.623***	-0.408***
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)
% EQUITY-OFFERED	2% offered	-0.266***		-0.306***	-0.288***	-0.316***	-0.370***	-0.308***
		(0.06)		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
	9% offered	-0.002		-0.037	-0.024	-0.071	-0.107**	-0.049
		(0.05)		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$PRE-MONEY	1.000€ premoney	-0.100*	-0.135**		-0.151***	-0.089	-0.159***	-0.117**
		(0.06)	(0.05)		(0.06)	(0.06)	(0.05)	(0.05)
	10.000€ premoney	0.057	0.046		-0.018	0.028	-0.027	0.043
		(0.06)	(0.06)		(0.05)	(0.06)	(0.05)	(0.05)
N-PROF-INVESTORS	0 professional investors	-0.307***	-0.316***	-0.294***		-0.323***	-0.334***	-0.231***
		(0.05)	(0.05)	(0.05)		(0.05)	(0.05)	(0.05)
	1 professional investors	-0.143***	-0.155***	-0.144***		-0.174***	-0.169***	-0.080*
		(0.05)	(0.05)	(0.05)		(0.05)	(0.05)	(0.05)
N-RET-INVESTORS	16 retail investors	-0.275***	-0.282***	-0.250***	-0.297***		-0.312***	-0.239***
		(0.05)	(0.05)	(0.05)	(0.05)		(0.05)	(0.05)
	122 retail investors	-0.057	-0.073	-0.049	-0.080		-0.144***	-0.065
		(0.06)	(0.05)	(0.06)	(0.05)		(0.06)	(0.05)
%INVEST-CONFIRM	0% confirmed	-0.713***	-0.746***	-0.726***	-0.745***	-0.719***		-0.754***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)		(0.05)
	88% confirmed	-0.049	-0.093*	-0.075	-0.096*	-0.063		-0.069
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)		(0.05)
SOCIALS	None	-0.384***	-0.380***	-0.392***	-0.332***	-0.338***	-0.476***	
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	
	Twitter (X) and/or LinkedIn	-0.239***	-0.244***	-0.262***	-0.187***	-0.265***	-0.257***	
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
	Facebook and/or Instagram	-0.156**	-0.121**	-0.186***	-0.149**	-0.145**	-0.198***	
		(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	
	N	1018	1018	1018	1018	1018	1018	1018
	Pseudo R-squared	0.04	0.04	0.04	0.04	0.04	0.02	0.04
	AIC	14999.32	15041.89	15009.59	15031.27	15035.57	15331.14	15048.89
	BIC	15110.90	15137.53	15105.23	15126.92	15131.21	15426.78	15136.57

* p<0.10, ** p<0.05, *** p<0.010

We employed Likelihood-ratio (LR) tests to compare the goodness of fit of the nested models and test for statistical differences between the full model and the reduced models. The LR tests, together with the information criteria comparison (Akaike's Information Criterion, AIC), allow us to reconstruct the attribute ranking as perceived by retail investors. Results are synthetized in Table 9.

Table 9: attribute importance – baseline model

	Attribute	LR test	AIC
1	Financial commitment	335.82***	15331.14
2	Social media	55.57***	15048.89
3	Equity offered	46.57***	15041.89
4	Retail investors	40.25***	15035.57
5	Professional investors	35.96***	15031.27
6	Pre-money	14.27***	15009.59

AIC full model = 14999.32

* p<0.10, ** p<0.05, *** p<0.010

The financial commitment attribute exhibits the highest LR test statistic at 335.82 ($p < 0.01$), indicating a substantial impact on the model's explanatory power. This is supported by a larger AIC score of 15331.14 if compared to the reference point of the full model (AIC of 14999.32). The second attribute in importance is Social Media, which is statistically distant (LR of 55.57 and AIC of 15048.89) from the first attribute. The last attribute in importance is pre-money, with a LR of 14.27 and AIC closer to the reference model (15009.59).

6.2. The moderation of FK

Our baseline specification analyzes the impact of different sources of information on the investment propensity of retail investors. In other words, it estimated which information sources individuals consider when selecting ECF campaigns to invest in, among those provided by the platforms. However, it is interesting to analyze the role of financial knowledge in their decision-making process and whether it plays a moderating role. For instance, retail investors with high levels of financial knowledge (FK) may consult sources that possess private information or imitate the behaviour of more informed economic agents. Table 10 reports the estimation results of the sub-groups per levels of FK, providing insights into the moderating role of the variable.

Table 10: sub-group regression models per levels of financial knowledge

		(1) Low FK Coef./(Std. err.)	(2) High FK Coef./(Std. err.)
	Y=choice		
	Status-quo	-0.172	-1.043***
		(0.12)	(0.12)
% EQUITY-OFFERED	2% offered	-0.169**	-0.374***
		(0.08)	(0.08)
	9% offered	-0.003	-0.003
		(0.08)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.168**	-0.038
		(0.08)	(0.08)
	10.000€ premoney	-0.007	0.125
		(0.08)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.082	-0.516***
		(0.08)	(0.07)

	1 professional investors	0.019	-0.291***
		(0.07)	(0.07)
N-RET-INVESTORS	16 retail investors	-0.166**	-0.390***
		(0.08)	(0.08)
	122 retail investors	-0.019	-0.091
		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.525***	-0.888***
		(0.07)	(0.07)
	88% confirmed	-0.090	0.000
		(0.07)	(0.07)
SOCIALS	None	-0.228***	-0.549***
		(0.08)	(0.08)
	Twitter (X) and/or LinkedIn	-0.198**	-0.274***
		(0.08)	(0.08)
	Facebook and/or Instagram	-0.148*	-0.159*
		(0.09)	(0.09)
	N	492	526
	Pseudo R-squared	0.04	0.07
	AIC	7331.59	7565.10
	BIC	7432.99	7667.43

* p<0.10, ** p<0.05, *** p<0.010

The results indicate that retail investors with higher levels of FK have no significant preference toward pre-money valuation compared to individuals with lower levels of FK. In contrast, individuals with higher levels of FK show a significantly strong preference for investment alternatives in which more professional investors with private information have already invested. Therefore, moderating role of FK let us assume that crowd-investors with high FK understand the importance and utility of private information.

Table 11 reports the results of the nested (reduced) model estimates to capture the importance of each attribute in the case of high financial knowledge.

Table 11 attribute importance – high financial knowledge - stepwise backward elimination models

		(1) High FK Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status-quo	-1.043***	-0.981***	-1.115***	-0.864***	-0.978***	-1.106***	-0.802***
		(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)
% EQUITY-OFFERED	2% offered	-0.374***		-0.400***	-0.407***	-0.442***	-0.486***	-0.430***
		(0.08)		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	9% offered	-0.003		-0.028	-0.040	-0.110	-0.133*	-0.072
		(0.08)		(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.038	-0.096		-0.123	-0.034	-0.110	-0.074
		(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)
	10.000€ premoney	0.125	0.093		0.002	0.074	-0.004	0.085
		(0.08)	(0.08)		(0.08)	(0.08)	(0.07)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.516***	-0.523***	-0.490***		-0.531***	-0.539***	-0.406***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.07)
	1 professional investors	-0.291***	-0.304***	-0.289***		-0.328***	-0.312***	-0.209***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.06)
N-RET-INVESTORS	16 retail investors	-0.390***	-0.381***	-0.363***	-0.428***		-0.459***	-0.324***
		(0.08)	(0.07)	(0.08)	(0.08)		(0.08)	(0.08)
	122 retail investors	-0.091	-0.103	-0.085	-0.133*		-0.248***	-0.117
		(0.08)	(0.08)	(0.08)	(0.08)		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.888***	-0.932***	-0.903***	-0.942***	-0.900***		-0.950***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
	88% confirmed	0.000	-0.061	-0.040	-0.079	-0.027		-0.056
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
SOCIALS	None	-0.549***	-0.538***	-0.558***	-0.448***	-0.476***	-0.632***	
		(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	
	Twitter (X) and/or LinkedIn	-0.274***	-0.287***	-0.301***	-0.178**	-0.302***	-0.311***	
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	
	Facebook and/or Instagram	-0.159*	-0.118	-0.201**	-0.131	-0.149*	-0.232***	
		(0.09)	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	
	N	526	526	526	526	526	526	526
	Pseudo R-squared	0.07	0.06	0.07	0.06	0.06	0.04	0.06
	AIC	7565.10	7608.66	7569.38	7613.19	7601.29	7850.70	7620.88
	BIC	7667.43	7696.37	7657.10	7700.91	7689.01	7938.42	7701.29

* p<0.10, ** p<0.05, *** p<0.010

The results of attribute importance in the investment decision-making process of retail investors with high FK, as measured by LR tests and AIC scores are then synthesized in Table 12.

Table 12 attribute importance – high financial knowledge

High FK			
	Attribute	**LR test**	**AIC**
1	Financial commitment	289.60***	**7850.699**
2	Social media	61.78***	**7620.88**
3	Professional investors	52.10***	**7613.192**
4	Equity retention	47.56***	**7608.657**
5	Retail investors	40.20***	**7601.292**
6	Pre-money	8.28**	**7569.378**
AIC full model = 7565.095			

The financial commitment attribute stands out with a substantial LR test statistic of 289.60, indicating a strong impact on the model's explanatory power. This is supported by an AIC score of 7850.699, underscoring the attribute's significance in influencing their investment choices. Moreover, this attribute shows four times the magnitude of the second emerging feature, which is social media presence (LR test statistic of 61.78 and AIC of 7620.88). However, it is noteworthy that individuals with high levels of FK value information from professional investors more, which ranks third in the attribute importance.

6.3. The moderation of DA

Similarly, it is interesting to consider the role of digital agency in retail investors' decision making and analyze its moderating role. For example, retail investors with high levels of digital agency (DA) are believed to be more likely to use digital finance tools and more confident in seeking relevant financial information or gaining knowledge through the experience or behaviour of better-informed agents. Table 13 reports the estimation results of the sub-groups per levels of FK, providing insights into the moderating role of the variable.

Table 13 sub-group regression models per levels of digital agency

		(1) Low DA Coef./(Std. err.)	(2) High DA Coef./(Std. err.)
	Y=choice		
	Status quo	-0.208*	-1.038***
		(0.12)	(0.12)
% EQUITY-OFFERED	2% offered	-0.241***	-0.321***
		(0.08)	(0.08)
	9% offered	0.022	-0.034
		(0.08)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.081	-0.137*
		(0.08)	(0.08)
	10.000€ premoney	-0.025	0.117
		(0.08)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.172**	-0.429***
		(0.08)	(0.07)
	1 professional investors	-0.011	-0.253***

		(0.07)	(0.07)
N-RET-INVESTORS	16 retail investors	-0.200**	-0.353***
		(0.08)	(0.08)
	122 retail investors	0.012	-0.124
		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.475***	-0.936***
		(0.07)	(0.07)
	88% confirmed	-0.036	-0.059
		(0.07)	(0.07)
SOCIALS	None	-0.377***	-0.397***
		(0.08)	(0.08)
	Twitter (X) and/or LinkedIn	-0.326***	-0.144*
		(0.08)	(0.08)
	Facebook and/or Instagram	-0.229***	-0.084
		(0.09)	(0.09)
	N	498	520
	Pseudo R-squared	0.05	0.07
	AIC	7356.54	7510.74
	BIC	7458.11	7612.92

* p<0.10, ** p<0.05, *** p<0.010

The results suggest that retail investors with higher levels of DA value information coming also from fewer social media compared to individuals with lower levels of DA. In particular, the latter value more the number (4) of social media accounts, whether the former value also the substance of the different social media. They are wary of investment campaigns without social media, but feel it is sufficient to guide their investment decision to have at least two social media accounts and, in particular, Facebook and/or Instagram. Twitter (X) and/or LinkedIn alone seem to be disliked when compared with the presence of four social media, but with partial statistical significance. At the same time, individuals with higher levels of DA show a significantly strong preference for investment alternatives in which multiple professional investors with private information have already invested, whether individuals with low levels of DA consider the presence of at least one professional investor to be sufficient.

Table 14 attribute importance – high digital agency - stepwise backward elimination models

		(1) High DA Coef./(Std. err.)	(2) Reduced model 1 Coef./(Std. err.)	(3) Reduced model 2 Coef./(Std. err.)	(4) Reduced model 3 Coef./(Std. err.)	(5) Reduced model 4 Coef./(Std. err.)	(6) Reduced model 5 Coef./(Std. err.)	(7) Reduced model 6 Coef./(Std. err.)
	Y=choice							
	Status quo	-1.038***	-0.979***	-1.108***	-0.881***	-0.965***	-1.059***	-0.890***
		(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.09)
% EQUITY-OFFERED	2% offered	-0.321***		-0.378***	-0.345***	-0.389***	-0.423***	-0.355***
		(0.08)		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
	9% offered	-0.034		-0.088	-0.061	-0.132*	-0.157**	-0.073
		(0.08)		(0.08)	(0.08)	(0.08)	(0.07)	(0.08)
$PRE-MONEY	1.000€ premoney	-0.137*	-0.187**		-0.212***	-0.127	-0.182**	-0.161**
		(0.08)	(0.08)		(0.08)	(0.08)	(0.08)	(0.08)
	10.000€ premoney	0.117	0.092		0.015	0.084	0.008	0.085
		(0.08)	(0.08)		(0.08)	(0.08)	(0.07)	(0.08)
N-PROF-INVESTORS	0 professional investors	-0.429***	-0.436***	-0.405***		-0.446***	-0.464***	-0.361***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.07)
	1 professional investors	-0.253***	-0.260***	-0.259***		-0.291***	-0.278***	-0.208***
		(0.07)	(0.07)	(0.07)		(0.07)	(0.07)	(0.06)
N-RET-INVESTORS	16 retail investors	-0.353***	-0.358***	-0.313***	-0.386***		-0.432***	-0.292***
		(0.08)	(0.07)	(0.08)	(0.08)		(0.08)	(0.08)
	122 retail investors	-0.124	-0.140*	-0.110	-0.155**		-0.283***	-0.139*
		(0.08)	(0.08)	(0.08)	(0.08)		(0.08)	(0.08)
%INVEST-CONFIRM	0% confirmed	-0.936***	-0.971***	-0.952***	-0.984***	-0.951***		-0.993***
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
	88% confirmed	-0.059	-0.110	-0.106	-0.127*	-0.080		-0.111
		(0.07)	(0.07)	(0.07)	(0.07)	(0.07)		(0.07)
SOCIALS	None	-0.397***	-0.397***	-0.415***	-0.315***	-0.337***	-0.500***	
		(0.08)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)	
	Twitter (X) and/or LinkedIn	-0.144*	-0.163**	-0.189**	-0.060	-0.167**	-0.199***	
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	
	Facebook and/or Instagram	-0.084	-0.051	-0.144*	-0.053	-0.076	-0.149*	
		(0.09)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	
	N	520	520	520	520	520	520	520
	Pseudo R-squared	0.07	0.06	0.06	0.06	0.06	0.03	0.06
	AIC	7510.74	7537.19	7526.42	7543.26	7535.43	7808.65	7540.98
	BIC	7612.92	7624.77	7614.00	7630.84	7623.01	7896.23	7621.27

* p<0.10, ** p<0.05, *** p<0.010

Table 14 reports the results of the nested (reduced) model estimates to capture the importance of each attribute in the case of high DA. The results of attribute importance in the investment decision-making process of retail investors with high DA, as measured by LR tests and AIC scores are then synthesized in Table 15.

Financial commitment emerges once again as the most influential attribute, as evidenced by the highest LR test statistic of 301.91, which is more than eight times larger than the second attribute, and an associated AIC of 7808.65. However, the results also show that information from professional investors becomes even more important to retail investors with high DA. On the other hand, information from social media loses one position and ranks third for individuals with higher levels of digital competence, confidence and accountability.

Table 15 attribute importance – high digital agency

High DA			
	Attribute	**LR test**	**AIC**
1	Financial commitment	301.91***	7808.65
2	Professional investors	36.52***	7543.26
3	Social media	36.24***	7540.98
4	Equity retention	30.45***	7537.19
5	Retail investors	28.69***	7535.43
6	Pre-money	19.68***	7526.42
		AIC full model = 7510.74	

7. Discussion

Given the transactional complexities associated with information acquisition, including its interpretation and dissemination, we believe that ECF platforms play a key role in ameliorating these challenges. Designed to facilitate the provision, exchange, and interpretation of information, they enable potential investors to discern the most suitable investment opportunities within early-stage innovative companies.

In fact, information is often considered a valuable resource that enhances decision-making processes across various domains, including finance (Macauley, 2006). In the context of the financial markets, the economic value of information lies in its ability to reduce uncertainty and provide insights into future events. Investors seek information to gain a competitive edge, mitigate risks, and capitalize on emerging opportunities. The value of information is contingent on its relevance, accuracy and timeliness (Rascão, 2021).

Indeed, the preferences of retail investors, generally not skilled and trained in finance, are shaped by the information available to them and understanding their behaviour is essential for developing a nuanced comprehension of market dynamics, especially in an innovative environment such as the ECF.

Administering a Discrete Choice Experiment to a sample of N=1,018 Italian household heads, representative of the Italian consumers and retail investors, we analyse their preferences toward different types of information (public vs private, hard vs soft) affecting their decision-making, allegedly guiding their herding behaviour. As expected, we find that these individuals are influenced more significantly by public information sources (the percentage of equity already paid by other investors and the number of social media networks managed by the startup) and less by private ones (the number of professional investors and the pre-money evaluation of the startup).

In particular, the financial commitment of the investor crowd appears to be the most influential source of information overall, with an impact on investor choice ranging from 4 to 8 times the magnitude of other sources of information. It represents a public information and soft in nature. Similarly, our results indicate that the second most influential attribute is again a public source of information, namely the number of social media accounts associated with the new venture. Conversely, the last two sources of information for magnitude, are the number of professional investors and the pre-money valuation that both encompass private information. Therefore, Hypothesis 1a is supported by the evidence from our sample and we imagine that retail crowd-investors consult and understand public rather than private information better; conversely, results offered mixed evidence for H1b, because the first source is soft one (investors commitment) and the second source is a hard one (number of social organized by the startup).

Moreover, we uncover a moderation role of financial knowledge and digital agency. In fact, individuals with higher levels of financial knowledge upscale the perceived importance of presence of financial professionals (soft, private information). Therefore, our data partially supports evidence for Hypothesis 2.

The aforementioned upscale is even higher for individuals who exhibit high levels of digital agency, which again offers partial support for Hypothesis 3. Indeed, retail investors with higher degrees of digital competence, trust, and responsibility tend to value information from professional investors (private and soft) significantly more. The results also allow us to infer that individuals with greater familiarity with digital technologies tend to value dynamic and fluid information, i.e., soft information, more highly.

8. Conclusive remarks

In conclusion, the findings of this study shed light on the intricate dynamics governing the decision-making processes of non-professional, non-skilled investors in the realm of ECF. The observed herding behavior among ECF investors, driven by a perceived need to compensate for gaps in knowledge, skills, and experience, underscores the critical role of information in guiding investment choices. Notably, our DCE with a representative sample of Italian household heads revealed a distinct preference for public information sources, particularly the percentage of equity already paid by other investors and the number of social networks managed by the startup. This inclination towards publicly available data suggests a reliance on collective wisdom and social signals in the decision-making process. Contrarily, private information sources, such as the involvement of professional investors and the pre-money evaluation of the startup, exerted a comparatively lesser influence on investor choices. This effect, however, is subject to the moderation of financial knowledge and digital agency.

Indeed, individuals with higher levels of financial literacy displayed an augmented emphasis on the presence of financial professionals in guiding their investment decisions. This effect was even more pronounced among individuals exhibiting high levels of digital agency, underlining the increasing importance of technological proficiency in shaping investor preferences. This nuanced interplay between financial literacy, digital agency, and information preferences highlights the need for targeted educational programs aimed at enhancing both financial literacy and digital competencies within a given population.

As countries strive to foster vibrant entrepreneurial ecosystems, our findings advocate for comprehensive educational initiatives that not only bolster financial literacy but also cultivate digital agency among the populace. Policymakers, institutions, and private entities should collaborate in designing and implementing programs aimed at elevating the sophistication of investors, thereby fostering a more informed and resilient investment landscape within the rapidly evolving domain of Equity Crowdfunding.

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