frontiers | Frontiers in Behavioral Economics

TYPE Original Research
PUBLISHED 14 January 2026
DOI 10.3389/frbhe.2025.1725333

OPEN ACCESS

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RECEIVED 20 October 2025
REVISED 04 December 2025
ACCEPTED 04 December 2025
PUBLISHED 14 January 2026

CITATION
Jiang Y and Shimizu S (2026) Financial literacy may not directly drive investment participation or retirement planning in Japan. *Front. Behav. Econ.* 4:1725333. doi: 10.3389/frbhe.2025.1725333

Financial literacy may not directly drive investment participation or retirement planning in Japan

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Introduction: Japan's rapidly aging society and pension-related deficits highlight the importance of household financial asset formation. Despite policies such as the Nippon Individual Savings Account, Japanese households still allocate over half their portfolios to deposits. While financial literacy has been linked to retirement planning and investment participation, existing research is largely correlational.

Method: This study uses individual-level data from the 2022 Financial Literacy Survey. We apply the Fast Causal Inference algorithm, which accommodates latent confounders, to examine causal relationships between financial literacy and financial activities, specifically investment participation and retirement planning.

Results: Our findings indicate that increasing financial literacy may not directly boost engagement in financial investments or retirement planning in Japan, which underscores the necessity for alternative strategies to motivate financial activities among Japanese households.

Discussion: This research offers valuable insights for policymakers focused on improving financial wellbeing by advancing the use of causal discovery algorithms in understanding financial behaviors.

KEYWORDS

causal discovery, fast causal inference, financial literacy, investment participation, retirement planning

1 Introduction

In 2019, Japan's Financial Services Agency (FSA) published a report titled "Asset Formation and Management in an Aging Society," which highlighted that an average older couple would need approximately 20 million yen for a 30-year post-retirement life, leading to a monthly deficit of around 50,000 yen not covered by public pension programs (Financial Services Agency of Japan, 2019a). According to Ministry of Health, Labour and Welfare (2024), the minimum wage varies from 790 yen per hour in Tottori to 1,113 yen per hour in Tokyo. This 50,000-yen deficit represents approximately 31.6% of a typical worker's monthly income in Tottori and 22.5% in Tokyo, emphasizing its substantial financial strain. Moreover, the Statistics Bureau of Japan (2023) indicates that the median savings for multi-person households stood at 11.07 million yen, making it challenging for many to build sufficient retirement savings. This situation garnered widespread media attention and public concern regarding the household financial asset formation in Japan. In 2022, the Council of New Form of Capitalism Realization adopted the "Doubling of Asset-based Incomes Plan," aiming to double the number of Nippon Individual Savings Account (NISA) holders and cumulative purchase amounts in five years. This plan is designed to

encourage Japanese households to diversify their savings into risky assets for economic growth and personal financial wellbeing.

The FSA has implemented various measures to promote the transition from savings to investment over the past 20 years. For example, from 2003 to 2013, preferential tax treatment for securities investment allowed that the tax rate on dividends and capital gains from stock or investment trusts was reduced from 20 to 10%. In 2014, the NISA was initiated as an investment tax-break scheme. In 2018, an installment-type NISA was launched. Despite these initiatives, the impact appears to be less dramatic than anticipated. As illustrated by the Bank of Japan (BOJ), households' asset composition has shown little change over the past 20 years. By December 2023, the share of "currency and deposits" in Japanese yen in the total financial assets held by households was still as high as 52.3% (Bank of Japan, 2023).

Due to the prolonged ultra-low interest rate environment for Japanese Yen deposits, portfolios heavily weighted in "currency and deposits" have shown notable low growth. Data published by FSA in 2019 indicates that total household financial assets in Japan grew only 1.4 times from 1998 to 2018, compared to 2.7 times in the United States (U.S.) and 2.3 times in the United Kingdom (U.K.) (Financial Services Agency of Japan, 2019b).

In Japan, characterized by a rapidly aging population and a pay-as-you-go public pension system, financial asset accumulation and proactive retirement planning is becoming increasingly critical. Academic studies and governmental surveys have been undertaken to understand why Japanese households are hesitant to invest in risky assets. With this context, financial literacy, defined as individuals' capacity to process information and make judicious decisions about financial planning, asset accumulation, and pension-related considerations (Lusardi and Mitchell, 2014), has emerged as a focal point. The Central Council for Financial Services Information, affiliated with the BOJ, has carried out nationwide large-scale questionnaire surveys, "Financial Literacy Survey," in 2016, 2019, and 2022 to assess the financial literacy of individuals in Japan, with results showing lower financial knowledge levels in Japan compared to the U.S. and other Organization for Economic Co-operation and Development (OECD) countries (Bank of Japan, 2022).

Lusardi and Mitchell (2011b) developed benchmark financial literacy questions in 2004 to measure three essential economic concepts: interest compounding, inflation, and risk diversification. Guided by the principles of simplicity, relevance, brevity, and capacity to differentiate, these questions have since been widely applied internationally, including in the "Financial Literacy Survey" conducted by the BOJ.

Prior studies utilizing diverse survey datasets have elucidated that enhanced financial literacy contributes to more effective retirement planning (Lusardi and Mitchell, 2011a) and encourages increased investment in complex financial assets (Van Rooij et al., 2011b). Based on these findings and the suboptimal financial literacy level among Japanese households, the 2022 national school curriculum update in Japan mandates a heightened focus on personal finance education in high schools to improve financial literacy within this young demographic.

While existing research on financial literacy has predominately identified positive correlational relationships with financial activities, employing causal discovery methods offers the potential to draw conclusions about causality. However, no prior research has employed causal discovery methods to work on this topic, either within Japan or internationally. Therefore, this study adopts a causal discovery approach to investigate the causal connections between financial literacy and financial activities, including retirement planning and investment participation in risky financial assets in Japan. In this manner, this study not only sheds light on the impact of Japan's recent implementation of finance education in high schools but also provides a framework that can be applied to similar studies. Although our study primarily focuses on analyzing and interpreting data from Japan, the implications of applying the causal discovery approach also extend to other countries.

2 Literature review

Over the last two decades, financial literacy has emerged as a key area of study, with a focus on the relationship with an individual's capability to make informed financial decisions. Previous studies posit that financial literacy is essential in enabling individuals to engage in financial investment and aiding in effective retirement planning.

Research consistently shows that financial literacy significantly influences stock market participation. For example, using data from the 2005 De Nederlandsche Banks Household Survey, Van Rooij et al. (2011b) demonstrate that individuals with higher levels of financial literacy are more likely to participate in stock investment. A similar pattern is observed in cross-country studies: Thomas and Spataro (2018), examining nine European countries, report that financial literacy positively impacts the likelihood of stock market participation. The same conclusion is also applicable to Japan. An analysis by Yamori and Ueyama (2022) of a 2019 online survey on wealth building, securities, investment, and financial literacy in Japan confirms that elevated financial literacy is generally linked to increased participation in the stock market.

Other studies have focused on the association between financial literacy and retirement planning. In the U.S., Lusardi and Mitchell (2011a) use data from the National Financial Capability Survey to show that financial literacy significantly influences retirement planning. This conclusion remains robust even when accounting for endogeneity and possible inaccuracies in measuring financial literacy. In Japan, Sekita (2011) reports a comparable result. Analyzing the January—February 2010 wave of the Survey of Living Preferences and Satisfaction, the study reveals that enhanced financial literacy increases the likelihood of holding a retirement savings plan in Japan.

Most of the aforementioned studies have consistently identified correlational associations related to financial literacy through regression-based approaches such as Ordinary Least Squares (OLS) (Van Rooij et al., 2011b; Thomas and Spataro, 2018; Yamori and Ueyama, 2022), making it difficult to draw definitive causal conclusions. Some studies have attempted to address specific types of endogeneity, such as reverse causality or selection bias, by adopting an Instrumental Variables (IV) approach (Lusardi and Mitchell, 2011a; Yamori and Ueyama, 2022). While IV methods can effectively migrate endogeneity by using instruments correlated

with the explanatory variable but uncorrelated with the error term (Van Rooij et al., 2011a,b), they typically require prior knowledge of the causal structure to identify strong, valid instruments. Because of this dependency limitation, latent confounders could affect both the instrument and the outcome, potentially leading to biased estimates.

Our decision to apply causal discovery models arises from this need to explore underlying causal structures without assuming prior knowledge—an essential step given the complex and barely understood relationships between financial literacy and financial activities among Japanese households. Causal discovery is thus not intended as a replacement for traditional econometric methods but as a complementary tool. By serving as a preliminary step, it enables us to identify potential causal relationships and structures that can then guide subsequent analyses using traditional methods, such as IV, to rigorously estimate magnitudes of causal effects.

3 Data

The "Financial Literacy Survey" is an extensive questionnaire survey used to evaluate the financial literacy of Japanese individuals. This online survey engaged 30,000 respondents aged 18–79, mirroring Japan's demographic distribution.[1] For this study, individual-level data from the 2022 survey was utilized, which was the third survey following those conducted in 2016 and 2019.

We used 13 variables from the survey data to represent respondents' demographics, socioeconomic status, behavioral biases, financial activities, and financial literacy levels. A complete list of variables, including question wording and variable construction details, is provided in Table 1. Tables 2, 3 present key descriptive statistics for all variables.

First, we identified five exogenous variables from the survey data reflecting demographic and socioeconomic factors: (1) *Male*, indicating gender; (2) *Fin_Edu*, participation in financial education at school or the workplace; (3) *Fin_Edu_Home*, participation in financial education at home; (4) *Age*, and (5) *Education*, representing educational background. We included two more variables to capture further socioeconomic information: *Income*, representing the individual's (or household's) income for the previous year, and *Asset_Amt*, indicating the current financial assets. These variables are essential, as prior studies have shown that both income and asset levels are closely associated with financial literacy (Sekita, 2011; Lusardi, 2019).

In the 2011 report "National Financial Literacy Strategy," the Australian Securities & Investments Commission identified six primary behavioral biases that may influence individuals' decisions, including those related to complex financial matters. These biases are disengagement, overconfidence, loss aversion, myopic decision-making, mental accounting, and herd behavior.

To capture myopic decision-making—the tendency to focus on short-term gains while overlooking future impacts—we included an indicator variable, *Myopic_Bias*. Herd behavior was similarly represented by the variable *Herding_Bias*. Both variables use a Likert scale with responses ranging from "1" (Agree) to "5" (Disagree). Named after social scientist Rensis Likert, this widely used psychometric scale allows respondents to express their level of agreement or disagreement along a specified range. In addition, we included *Confidence* as a measure of respondents' confidence in their financial literacy level. The choices range from "1" (Very high) to "5" (Very low), with "6" representing "Don't know." The combination of objective financial literacy and subjective confidence can be used to measure individuals' overconfidence (Biais et al., 2005), and is reported to be positively correlated with stock market participation (Xia et al., 2014). Unfortunately, for the remaining three biases, we could not identify suitable corresponding questions within the survey.

A variable *Invest* was constructed to capture the number of risky asset types in which an individual has invested. Another variable, *Planning*, was created to assess whether the individual is well prepared for retirement, with values ranging from "0" to "4," where a higher value indicates more comprehensive retirement planning and preparation.

Finally, and of significant importance, *Fin_Literacy* represents the number of correct answers to the 25 questions designed to evaluate the individual's financial literacy level, covering eight categories of the Financial Literacy Map. See Supplementary material for all the questions and corresponding categories. Although the BOJ does not publicly disclose the correct answer to each question, we deduced them from our background knowledge in finance. Moreover, the "Financial Literacy Survey: 2022 Results" include each option's response ratio and the correct answer rate for every question (Bank of Japan, 2022). We compared the response ratios of the options deemed correct with the correct answer rates to ascertain the accuracy of our answers.

Apart from the three dummy variables—*Male*, *Fin_Edu*, *Fin_Edu_Home*—all other variables are treated as continuous. These continuous variables have been standardized before the subsequent analysis. We eliminated data entries with missing values for any of the variables, resulting in a reduction of the sample size from 30,000 to 19,333 ($\approx$ 64% % of the original). This exclusion process could potentially introduce bias, particularly concerning the data entries for income and financial assets. The selection of the "Don't know/Prefer not to say" option to these questions may not occur randomly. Instead, it is conceivable that individuals with either particularly low or high income (or financial assets) might tend to choose "Prefer not to say." To assess whether this potential bias affects the causal discovery results, we additionally conduct a multiple-imputation (MI) sensitivity analysis.

4 Method

To elucidate causal relationships, traditional methods involve interventions or randomized controlled trials (Glymour et al., 2019). Within macroeconomics, policy analysis is particularly intertwined with causal inference, as it seeks to predict the impacts of policy interventions (Moneta and Tieleman, 2024), including those related to financial education. However, conventional approaches can be prohibitively expensive, time-consuming, or impractical. For example, conducting randomized A/B tests related to financial education raises concerns regarding social ethics and fairness. Given these challenges, causal

1 The questions and options can be found on page 38–51 of Financial Literacy Survey.

TABLE 1 List of variables.

Variable	Wording of question	Construction of variable
Male	Q42. What is your gender? 1. Male 2. Female	A dummy variable that takes the value 1 if the answer is "1. Male."
Fin_Edu	Q39. Was financial education offered by a school or college you attended, or a workplace where you were employed? 1. Yes, but I did not participate in the financial education offered 2. Yes, and I did participate in the financial education 3. No 4. Don't know	A dummy variable that takes the value 1 if the answer is "Yes, and I did participate in the financial education."
Fin_Edu_Home	Q40. Did your parents or guardians teach you how to manage your finances? 1. Yes 2. No 3. Don't know	A dummy variable that takes the value 1 if the response is "Yes."
Age	Q43. What is your age? 1. 18–19 2. 20–24 3. 25–29 4. 30–34 5. 35–39 6. 40–44 7. 45–49 8. 50–54 9. 55–59 10. 60–64 11. 65–69 12. 70–74 13. 75–79	Calculated as the mean of the age range indicated by the response to the question.
Education	Q44. What is your educational background? 1. Primary and secondary schools only 2. High school 3. Specialized training college 4. Junior college / college of technology 5. University 6. Graduate school 7. Other	Calculated as the total years required to complete the selected educational level. A missing value was assigned for "7. Other."
Income	Q51. Which of these categories do your (your household) income for last year fall into? 1. Didn't earn any income 2. Less than 2.5 million yen 3. At least 2.5 million but less than 5 million yen 4. At least 5 million but less than 7.5 million yen 5. At least 7.5 million but less than 10 million yen 6. At least 10 million but less than 15 million yen 7. At least 15 million yen 8. Don't know/Prefer not to say	Calculated as the mean of the range for each category: a value of "0" for "1. Didn't earn any income," "125" for "2. Less than 2.5 million yen,"..... "1,250" for "6. At least 10 million but less than 15 million yen." For "7. At least 15 million yen," the lower limit value, "1500," was assigned. A missing value was assigned for "8. Don't know/Prefer not to say."
Asset_Amt	Q52. Which of these categories do your (your household's) financial assets (deposits, stocks, etc.) currently fall into? 1. Don't have any financial assets 2. Less than 2.5 million yen 3. At least 2.5 million but less than 5 million yen 4. At least 5 million but less than 7.5 million yen 5. At least 7.5 million but less than 10 million yen 6. At least 10 million but less than 20 million yen 7. At least 20 million yen 8. Don't know/Prefer not to say	Calculated as the mean of the range for each category: a value of "0" for "1. Don't have any financial assets," "125" for "2. Less than 2.5 million yen,"..... "1500" for "6. At least 10 million but less than 20 million yen." For "7. At least 20 million yen," the lower limit value, "2000," was assigned. A missing value was assigned for "8. Don't know/Prefer not to say."
Myopic_Bias	How much do you agree or disagree that each of the following statements applies to you personally? Q1_10. If I had the choice of (1) receiving 100,000 yen now or (2) receiving 110,000 yen in 1 year, I would choose (1), provided that I can definitely receive the money Agree Disagree 1. 2. 3. 4. 5.	Assigned as the value of the answer to Q1_10.
Herding_Bias	How much do you agree or disagree that each of the following statements applies to you personally? Q1_3. When there are several similar products, I tend to buy what is recommended as the best-selling product, rather than what I actually think is a good product Agree Disagree 1. 2. 3. 4. 5.	Assigned as the value of the answer to Q1_3.
Confidence	Q17. How would you rate your overall knowledge about financial matters compared with other people? 1. Very high 2. Quite high 3. About average 4. Quite low 5. Very low 6. Don't know	Assigned as the value of the answer to Q17. A missing value is assigned if option "6" is selected.
Invest	Q34. Have you ever purchased any of the following financial products? -Stocks -Investment trusts -Foreign currency deposits/MMFs I have purchased them 1. I understood the product details well enough to explain to other people 2. I understood the product details to a certain extent	Calculated as the number of risky assets types an individual has invested in, based on the responses to Q34, which can take a value between "0" and "3."

(Continued)

TABLE 1 (Continued)

Variable	Wording of question	Construction of variable
	3. I did not understand the product details very well 4. I did not understand the product details at all I have never purchased them 5. I have never purchased them	
Planning	Q7. What expenses do you think you will have to cover in the future? 1. Living expenses for retirement 2. Educational expenses for children 3. Costs of buying a house 4. Costs of health and nursing care for yourself 5. Costs of health and nursing care for family members 6. Costs of buying a car 7. Wedding expenses for yourself 8. Wedding expenses for children 9. Other ( ) 10. None in particular Q8_1. With regard to the expenses you think you will have to cover in the future, are you aware of the amounts that will be required in your case? For living expenses for retirement 1. Yes 2. No Q9_1. Do you have a financial plan for the expenses you think you will have to cover in the future? For living expenses for retirement 1. Yes 2. No Q10_1. Have you set aside funds for the expenses you think you will have to cover in the future? For living expenses for retirement 1. Yes 2. No	Calculated according to the following logic: If "1. Living expenses for retirement" is chosen in Q7, 1 is added to *Planning*. Additionally, for each "Yes" response to Q8_1, Q9_1, and Q10_1, *Planning* is incremented by 1. Therefore, *Planning* can range from "0" to "4."
Fin_Literacy	The number of correct answers to the 25 questions designed to evaluate the individual's financial literacy level. (For details on these 25 questions, see Supplementary material.)	Calculated as the number of correct answers to the 25 questions, ranging from "0" to "25."

TABLE 2 Descriptive statistics for continuous variables.

Variable	*N*	Mean	Std	Min	25%	Median	75%	Max
Herding_Bias	19,333	3.36	1.10	1.0	3.0	3.0	4.0	5.0
Myopic_Bias	19,333	2.87	1.62	1.0	1.0	3.0	5.0	5.0
Confidence	19,333	3.36	0.95	1.0	3.0	3.0	4.0	5.0
Age	19,333	50.33	16.50	18.5	37.0	52.0	62.0	77.0
Fin_Literacy	19,333	15.11	6.65	0.0	10.0	16.0	21.0	25.0
Education	19,333	14.30	2.05	9.0	12.0	14.0	16.0	18.0
Income	19,333	518.56	360.36	0.0	375.0	375.0	625.0	1,500.0
Asset_Amt	19,333	779.30	770.31	0.0	125.0	375.0	1,500.0	2,000.0
Planning	19,333	1.41	1.44	0.0	0.0	1.0	3.0	4.0
Invest	19,333	1.00	1.15	0.0	0.0	1.0	2.0	3.0

TABLE 3 Distribution of categorical variables.

Variable	Value	Count	Percentage (%)
Male	0	8,790	45.47
	1	10,543	54.53
Fin_Edu	0	17,674	91.42
	1	1,659	8.58
Fin_Edu_Home	0	15,490	80.12
	1	3,843	19.88

discovery methods have garnered growing attention. These methods facilitate the identification of causal structures from observational data, providing a practical alternative to traditional experimental designs.

Applying causal discovery models requires establishing specific foundational assumptions (Heinze-Deml et al., 2018). As noted in Section 3, the absence of survey questions addressing disengagement, loss aversion, and mental accounting—factors known to influence financial activities—suggests a likely violation of the assumption of *causal sufficiency*. The causal sufficiency assumption necessitates the absence of unobserved (or latent) variables in the analysis (Spirtes et al., 2001). While the linear, non-Gaussian, and acyclic model (LiNGAM) (Shimizu et al., 2006), a type of the structural equation model (Drton and Maathuis, 2017), is capable of identifying the unique directed acyclic graph (DAG), it requires causal sufficiency, which is not satisfied in the context of this study.

Among the constraint-based methods, the PC algorithm, named after its inventors Peter Spirtes and Clark Glymour (Spirtes et al., 2001), requires assumptions of causal sufficiency. The Fast Causal Inference (FCI) (Spirtes, 2001) extends the PC algorithm by relaxing the causal sufficiency assumption, thus permitting the presence of hidden variables (Glymour et al., 2019). Therefore, we employ the FCI algorithm to explore the mechanism behind financial literacy and financial activities, using the implementation

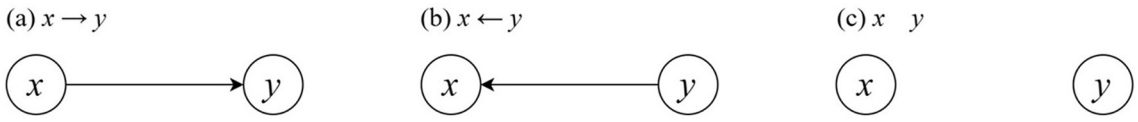

FIGURE 1
Three potential graph structures.

provided by the causal-learn package (version 0.1.3.6) in Python (Zheng et al., 2024).[2]

The constraint-based models, such as the PC and FCI algorithms, rely on testing for conditional independencies within the data to refine the causal structures. The PC algorithm starts with a fully connected graph among variables and iteratively removes edges when it detects conditional independence between pairs of variables, narrowing down the graph to align with observed dependencies (Spirtes et al., 2001). For instance, when analyzing two variables, the PC algorithm evaluates three potential structures shown in Figure 1: (a) $x \rightarrow y$, (b) $x \leftarrow y$, and (c) $x \quad y$, all of which satisfy the assumptions of a DAG with no hidden common causes. The graph that best matches the data based on the conditional independence test is selected:

(1) If x and y are independent in the data, select (c).

(2) If x and y are dependent in the data, select (a) and (b).

It cannot distinguish between graphs (a) and (b) as both maintain dependency between x and y. For datasets with multiple variables, the PC algorithm conducts conditional independence tests across variable pairs iteratively, removing edges to maintain alignment with conditional independencies. The FCI algorithm extends the PC algorithm by accounting for latent confounders—unobserved variables that can include spurious associations among observed variables. This enhancement makes FCI particularly valuable for causal inference in observational data, where such confounders often exist.

Given the mixed nature of our dataset, consisting of three discrete dummy variables and ten continuous variables, we initially considered applying FCI with a kernel-based conditional independence test (Zhang et al., 2011), which is suited for mixed data types. However, due to the cubic computational complexity of kernel methods relative to sample size and our substantial sample size of nearly 20,000 respondents, implementing this approach proved impractical with available computational resources. As an alternative approach, we divide our data into eight groups based on the combination of values of the three dummy variables: *Male*, *Fin_Edu*, and *Fin_Edu_Home*. For each group, we apply FCI with Fisher's Z conditional independence test (Fisher, 1921), which is suitable for continuous variables. This stratified continuous-variable approach was chosen as a transparent and reproducible strategy given our data structure, research focus, and analytic constraints. A significance level of 0.05 is selected for the individual partial correlation test in this study.

The FCI algorithm's effectiveness in determining causal relationships is well-supported for large samples (Spirtes, 2001). As sample sizes decrease, the power of its conditional independence tests weakens, potentially leading to less accurate or inconclusive outcomes. Additionally, the algorithm's feasibility becomes challenging with large datasets containing many variables. Thus, limiting the conditioning set in independence tests can enhance reliability for finite samples. To illustrate common sample sizes and configurations, studies have applied FCI and PC algorithms to similarly structured data: FCI on 1,008 participants in Alzheimer's research (Shen et al., 2020), a modified PC on quarterly economic data from Pakistan (1990–2018) for monetary policy analysis (Fazal et al., 2021), and a temporal PC on data from 2,928 Danish men to study the impact of socioeconomic factors on depression (Petersen et al., 2021). With our dataset comprising 19,333 respondents and 13 variables, its suitability for FCI is comparable to these prior studies.

Furthermore, previous research demonstrates that incorporating background knowledge into causal discovery enhances the accuracy of exploring causal relations and lends more realism to the interpretation of the results (Shen et al., 2020). To align with this, we define *Age* and *Education* as exogenous variables when applying the FCI algorithm to the pre-segmented data of the eight groups.

Additionally, bootstrapping (Felsenstein, 1985; Efron and Tibshirani, 1994) is used to confirm the statistical stability of the causal discovery results before drawing conclusions. This method resamples from the original dataset and regenerates partial ancestral graphs (PAGs) from the FCI algorithm for each sample. The resulting bootstrap probabilities of the existence of each edge indicate how frequently an edge appears across bootstrapped samples (similar to confidence intervals), with higher probabilities boosting confidence in its statistical reliability as a causal relationship. In this study, we conduct 100 bootstrap samplings to estimate the bootstrap probability for each edge in the PAGs. Edges with probabilities of 0.2 or lower were excluded from illustrations due to their low reliability, focusing instead on those with higher bootstrap probabilities for more robust conclusions. We acknowledge that the FCI algorithm involves multiple conditional independence tests, which may increase the risk of false positives. While we use a standard conservative significance level of 0.05, no formal multiple-testing correction was applied. Instead, we mitigate this risk by focusing on edges that appear consistently across 100 bootstrap samples.

Although identifying specific causal effects using the FCI algorithm can be challenging without incorporating stronger assumptions (Malinsky and Spirtes, 2017), the FCI algorithm offers valuable insights into the presence and direction of causal

2 See https://causal-learn.readthedocs.io/en/latest/. The Python script is publicly available for reproducibility at https://drive.google.com/file/d/1ecjVRCCrUigLHm4tOuwExjaM3v9I2uWQ/view?usp=sharing.

relationships in a dataset. This is consistent with the aim of our study to understand the existence and direction of causal relationships between financial literacy and financial activities, without quantifying the magnitude of these effects. Once causal directions are established, magnitudes of effect sizes can be evaluated using structural equation modeling or IV regressions with the causal structures derived from FCI.

5 Results

Prior to applying the causal discovery framework described in Section 4, we estimated OLS regressions to verify that financial literacy is linked to financial activities. In these preliminary models, each financial activity, *Invest* and *Planning*, was regressed on *Fin_Literacy* while conditioning on gender, age, education, income, asset levels, and behavioral-bias measures. The OLS results in Tables 4, 5 indicate that financial literacy has a positive and highly significant association with both investment participation and retirement planning. Although IV estimation is a common approach for addressing endogeneity, we did not pursue an IV strategy due to the lack of strong theoretical or empirical justification for a valid instrument. Instead, we turn to a causal discovery method to further investigate the underlying mechanisms driving the observed relationships.

As mentioned in Section 4, we divided the original survey data into eight groups based on three dummy variables: *Male*, *Fin_Edu*, and *Fin_Edu_Home*. The sample sizes and conditions for each group are summarized in Table 6. Notably, over 75% of the 19,333 respondents reported having not received financial education either at school or at home, corresponding to Groups 4 and 8. These groups show comparatively lower financially literacy, as indicated by the number of correct answers to financial knowledge questions (*Fin_Literacy)* shown in Figure 2.

In addition, Figure 2 demonstrates that females, represented by Groups 5 to 8, exhibit lower levels of financial literacy compared

TABLE 4 OLS regression results: *Invest*.

Variable	Coef	SE	t	$P > \|t\|$	[0.025	0.975]
Intercept	−0.0600	0.010	−5.913	0.000	−0.080	−0.040
Fin_Literacy	0.1316	0.008	17.031	0.000	0.116	0.147
Male	0.2240	0.013	17.104	0.000	0.198	0.250
Fin_Edu	0.4452	0.023	19.176	0.000	0.400	0.491
Fin_Edu_Home	−0.0176	0.016	−1.084	0.278	−0.049	0.014
Age	0.0122	0.007	1.645	0.100	−0.002	0.027
Education	0.0582	0.007	8.516	0.000	0.045	0.072
Income	0.0262	0.007	3.732	0.000	0.012	0.040
Asset_Amt	0.2515	0.008	31.331	0.000	0.236	0.267
Myopic_Bias	−0.0053	0.006	−0.817	0.414	−0.018	0.007
Herding_Bias	−0.0715	0.006	−11.296	0.000	−0.084	−0.059
Confidence	−0.2777	0.007	−40.832	0.000	−0.291	−0.264

TABLE 5 OLS regression results: *Planning*.

Variable	Coef	SE	t	$P > \|t\|$	[0.025	0.975]
Intercept	0.0011	0.011	0.098	0.922	−0.021	0.023
Fin_Literacy	0.1319	0.009	15.414	0.000	0.115	0.149
Male	0.0201	0.014	1.388	0.165	−0.008	0.049
Fin_Edu	0.0577	0.026	2.244	0.025	0.007	0.108
Fin_Edu_Home	0.1056	0.018	5.872	0.000	0.070	0.141
Age	0.0788	0.008	9.634	0.000	0.063	0.095
Education	0.0167	0.008	2.201	0.028	0.002	0.031
Income	0.1177	0.008	15.121	0.000	0.102	0.133
Asset_Amt	0.0809	0.009	9.104	0.000	0.063	0.098
Myopic_Bias	0.0346	0.007	4.857	0.000	0.021	0.049
Herding_Bias	−0.0180	0.007	−2.562	0.010	−0.032	−0.004
Confidence	−0.1116	0.008	−14.820	0.000	−0.126	−0.097

to males categorized in Groups 1 to 4, consistent with conclusions from previous research (Lusardi and Mitchell, 2011b; Yamori and Ueyama, 2022).

Utilizing the processed survey data, the PAGs derived from the FCI algorithm are illustrated in Figure 3 for Groups 1–4 and Figure 4 for Groups 5–8. A PAG, the output of the FCI algorithm, represents ambiguous causal relationships when there is uncertainty due to hidden confounders. It serves as a graphical summary of equivalent classes of maximal ancestral graphs (MAGs), which denotes a family of MAGs that are indistinguishable given the available data. A MAG extends a DAG by allowing for unobserved variables, while a DAG models causal relationships where each edge has a direction from cause to effect, and the graph has no cycles. In a MAG, $i \to j$ is drawn when i is an ancestor of j and j is not an ancestor of i in the underlying DAG. An "ancestor" refers to a variable that can causally influence another variable either directly or indirectly through a chain of other variables. PAGs can feature four types of edges (Malinsky and Spirtes, 2016): $\to$, $\circ\!\!\to$, $\circ\!\!-\!\!\circ$, and $\leftrightarrow$. $i \to j$ is drawn when i is an ancestor of j and j is not an ancestor of i. An edge $i \leftrightarrow j$ is drawn when i is not an ancestor of j and j is not an ancestor of i, indicating the influence of an unobserved confounder. The open dot $\circ$ is used in $i \circ\!\!\to j$ when $i \to j$ is present in some MAGs, while $i \leftrightarrow j$ exists in the others.

To ascertain the reliability of the generated PAGs, we employed the bootstrap method to assess the statistical robustness of the FCI algorithm's outputs. The comprehensive lists of edges generated from 100 bootstrap samplings, along with their bootstrap probabilities for each group, are provided in Supplementary material. The interpretations of the findings in this section, as well as the discussions and conclusions in subsequent sections, are based on edges with a bootstrap probability larger than 0.2.

We did not find a direct causal flow from *Fin_Literacy* to *Invest* or *Planning* in any of the PAGs across the eight groups, suggesting that financial literacy level is not a direct cause of investment participation in risky financial assets or retirement planning in Japan. Meanwhile, in the PAGs of Groups 1, 3, 4, 7, and 8, the presence of "$\leftrightarrow$" between *Fin_Literacy* and *Invest* might indicate the presence of latent confounders influencing both variables. Likewise, "$\leftrightarrow$" between *Fin_Literacy* and *Planning* in Groups 3, 4, 5, and 7 implies potential unobserved variables. Moreover, "$\circ\!\!\to$" extends from *Invest* to *Fin_Literacy* in Groups 4, 6, and 8. This edge suggests the potential causal relationship where participation in financial investment might enhance financial literacy levels. Similarly, "$\circ\!\!\to$" from *Planning* to *Fin_Literacy* in Groups 4 and 6, and "$\to$" in Groups 6, 7, and 8, reveal the possibility of a causal impact where retirement planning contributes to the improvement of financial literacy.

Concerning the causal relationship of confidence in financial literacy, divergent outcomes were observed across different bootstrap samplings and groups. Specifically, for Groups 1, 2, 3, 4, 6, and 8, the PAGs of some bootstrap samples depict a possible causal flow from confidence to investment in risky financial assets, represented by "$\to$" or "$\circ\!\!\to$" edges from *Confidence* to *Invest*. In contrast, confidence level can be a result of financial investment participation, illustrated by the "$\to$" from *Invest* to *Confidence* in some bootstrapping results of Groups 1, 2, 5, 6, and 8. Unobserved confounders can exist between *Invest* and *Confidence* represented by "$\leftrightarrow$" edges in PAGs generated from specific bootstrap samples in Groups 3 and 8. Regarding the causal link between confidence

TABLE 6 Sample sizes of eight groups.

Group	*Male*	*Fin_Edu*	*Fin_Edu_Home*	Sample size
Group 1	1	1	1	443
Group 2	1	0	1	1,482
Group 3	1	1	0	657
Group 4	1	0	0	7,961
Group 5	0	1	1	259
Group 6	0	0	1	1,659
Group 7	0	1	0	300
Group 8	0	0	0	6,572

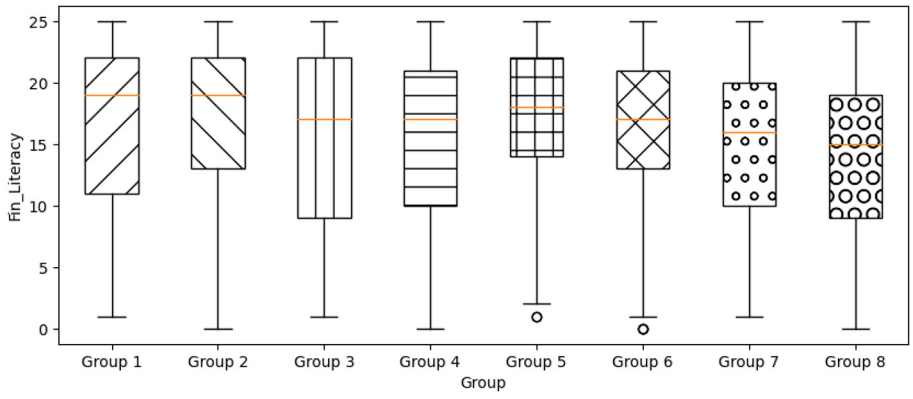

FIGURE 2
Boxplots of *"Fin_Literacy"* for eight groups.

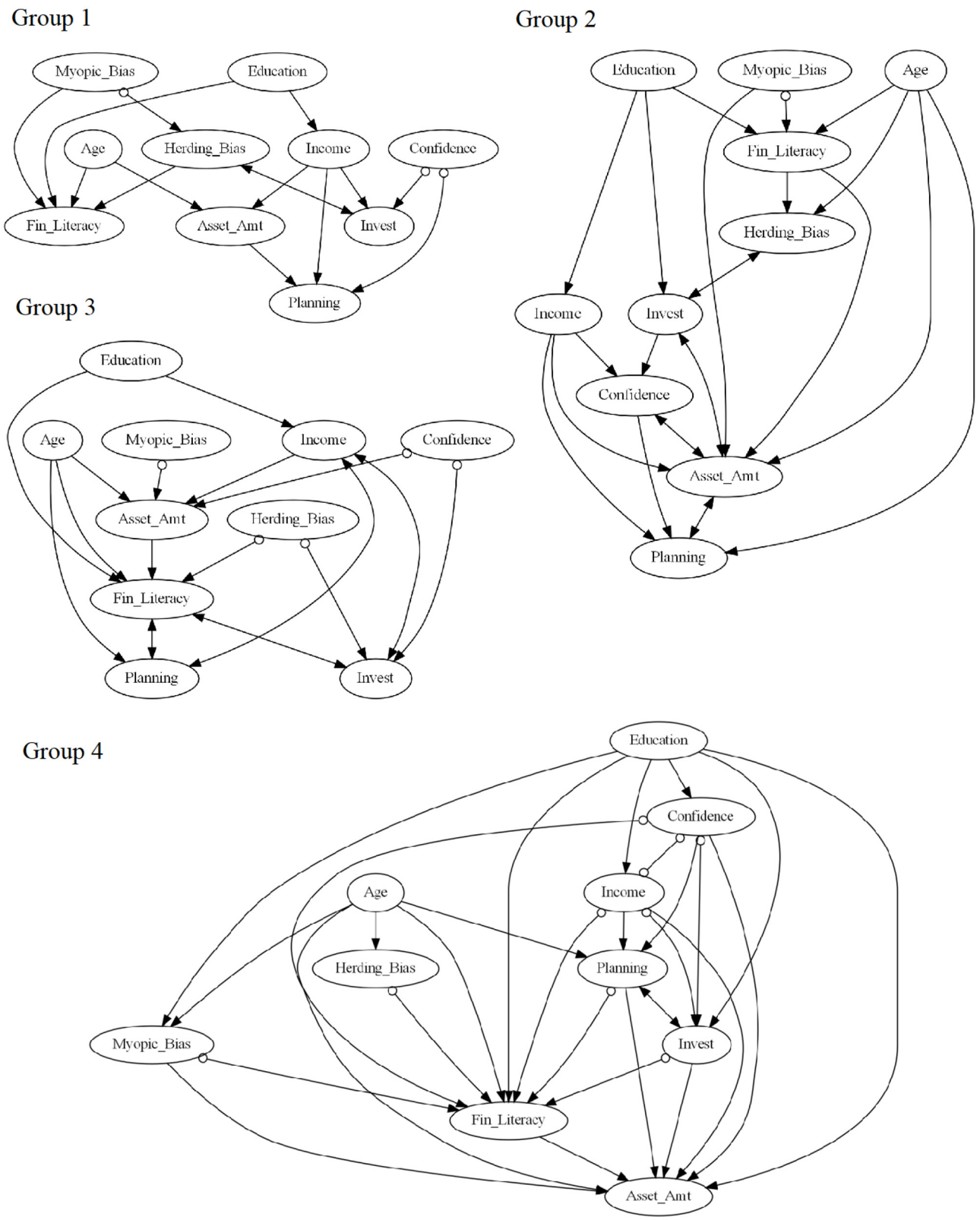

FIGURE 3
Output PAGs of FCI for Groups 1–4.

and retirement planning, both directions, "→" from *Confidence* to *Planning* and "→" from *Planning* to *Confidence*, appeared in PAGs from different bootstrap samples for Groups 1, 2, 6, and 8. In Group 4, "→" and "↔" are both possible between *Confidence* and *Planning* in the results, indicating the possible causal flow from confidence to retirement planning and the potential latent

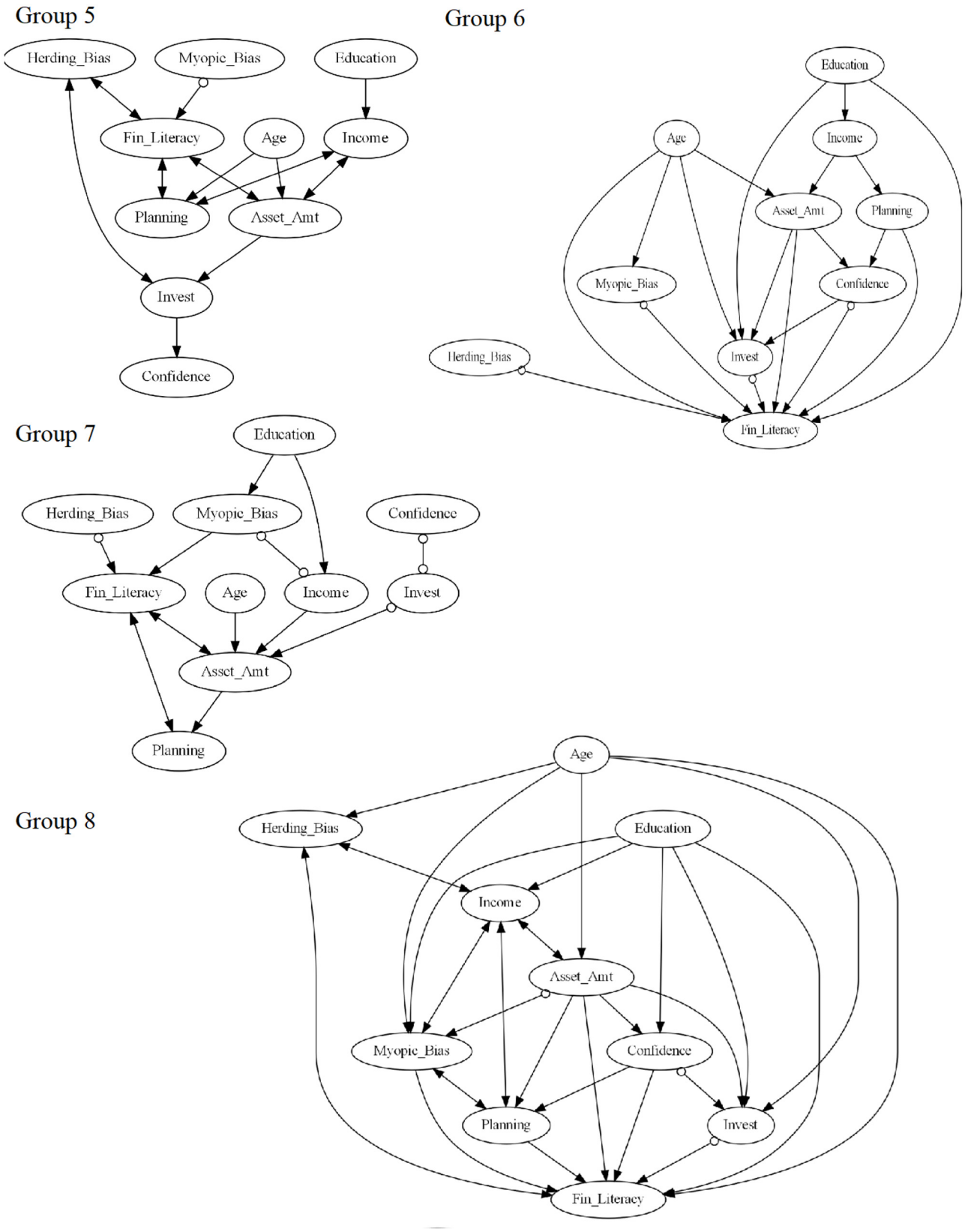

FIGURE 4
Output PAGs of FCI for Groups 5–8.

confounders between them. "↔" between *Confidence* and *Planning* can be found in Groups 2, 6, and 8, signaling the latent variables.

Beyond our initial focus on financial literacy, the results uncovered the causal influence of age on retirement planning, which is reflected by the indirect "→" from *Age* to *Planning* in the PAGs of Groups 1, 4, 7, and 8, and a direct "→" in Groups 2, 3, 4, 5, and 7. Additionally, direct causal influences from *Age* to *Invest* were confirmed in the results of female Groups 5, 6, and 8.

To assess the robustness of our findings, we also conducted MI sensitivity analysis using MI combined with the FCI algorithm implemented in the micd package (Foraita et al., 2020) in R (version 4.5.2) (see Supplementary material Part 3). The findings from the MI-based PAGs were consistent with those obtained from the complete-case analysis; none of the principal relationships identified in the original research were violated. This suggests that the exclusion of cases with missing data did not materially affect the substantive conclusions. While missingness was not completely random, its impact on our findings appears negligible.

6 Discussion

Although the literature introduced in Section 2 demonstrates that the financial literacy level is highly associated with financial activities, which could be a causal relationship, we did not confirm the direct causal impact of financial literacy on either investment in risky financial assets or retirement planning in the results of the FCI algorithm. Therefore, enhancing the financial literacy level of individuals in Japan through mandatory financial education in high school may not inevitably improve participation in financial investment and retirement planning in Japan. Meanwhile, we found the possibility of latent confounders between financial literacy and financial activities, either participation in financial investment or retirement planning, for Groups 1, 3, 4, 5, 7, and 8. Moreover, in Groups 4, 6, 7, and 8, financial activities may have a causal impact on financial literacy levels. The findings of latent confounders and reverse causation could help explain the high correlation between the variables verified in previous research.

When it comes to confidence in financial literacy, although results differed across bootstrap samples and groups, it was identified as a potential cause of investment participation in Groups 1, 2, 3, 4, 6, and 8, and of retirement planning in Groups 1, 2, 4, 6, and 8. This suggests that individuals who feel more confident in their financial knowledge may be more likely to invest or plan for retirement. However, according to the "Financial Literacy Survey: 2022 Results," a mere 12.1% of respondents rated their financial knowledge as "Very high" or "Quite high" compared with others. This figure is significantly lower than the 76% reported in the U.S. This gap highlights an opportunity for interventions, such as providing simulated financial experiences and creating environments for discussions about finances, to increase confidence in financial literacy among Japanese households, may potentially boost investment participation and retirement planning.

Our results also indicate a direct or indirect causal effect of age on financial activities. Hsu (2016) has noted that women often enhance their financial knowledge when it becomes relevant, typically around the time of their spouses' passing. In a parallel manner, the influence of age on retirement planning and investment participation might stem from a sense of "relevancy." As individuals age, they may perceive an escalating need for financial planning. Women may start investing in riskier assets to pursue higher returns, as their income growth does not typically match the pace experienced by men in Japan.

While our regression analysis confirms a strong association between financial literacy and financial activities, the application of the FCI algorithm offers a novel perspective by uncovering potential causal structures without relying on predefined background assumptions. It should be noted that FCI yields a qualitative causal structure rather than quantitative effect sizes. Therefore, we interpret the PAG outputs as suggestive patterns of causation and avoid making definitive causal claims or precise policy effect estimates based solely on these algorithmic findings.

To extend this study further, variables representing disengagement, loss aversion, and mental accounting can be included in the dataset, as these factors may affect individuals' decision-making. Given that the PAGs imply the presence of latent confounders between financial literacy and financial activities, potential variables can be identified by delving into financial and economic theories. Developing tailored survey questions and conducting follow-up surveys will also support these future studies.

Moreover, broadening the definition of financial literacy could yield deeper insights into its impact on financial activities. Traditionally, financial literacy has been primarily quantified in terms of financial knowledge. The OECD's redefinition, as articulated by Atkinson and Messy (2012), expanded this concept to include not only knowledge but also financial attitudes and behaviors. In contrast, our study focuses on financial knowledge and self-assessed confidence, which represents a narrower operationalization. The broader definition adopted in OECD studies has been positively associated with sound financial behaviors across countries. This divergence in findings may stem from contextual differences in cultural or institutional settings, or from differences in measurement scope. Future research could further explore this gap by incorporating practitioner insights and engaging experts to improve the external validity of causal claims in different policy environments.

Finally, future studies should apply the same method to other datasets to test the generalizability of our findings. For instance, comparing results from different time periods, such as the 2019 iteration of the "Financial Literacy Survey," could help reveal how shifts in economic conditions, such as those following the COVID-19 pandemic, impact financial decision-making mechanisms among Japanese households. Moreover, comparative studies applying the FCI algorithm to datasets from different countries or populations would allow us to assess whether the causal structures identified in Japan hold across diverse contexts, providing a more robust test of external validity.

7 Conclusion

In this research, we applied the FCI algorithm with Fisher's Z conditional independence test to individual-level data from the 2022 "Financial Literacy Survey" conducted by the BOJ, to investigate the causal relationships between financial literacy and financial activities, specifically focusing on retirement planning and investment in risky financial assets in Japan. The original dataset was divided into eight groups based on three exogenous discrete

variables to facilitate the use of Fisher's Z test for continuous variables. Two other variables were designated as exogenous, and this information was incorporated as background knowledge about the edges. The robustness of the edges in PAGs derived from the FCI algorithm was verified by estimating their probabilities using the bootstrap method.

Our findings indicate that enhancing financial literacy alone does not necessarily increase engagement in financial activities in Japan. While financial education may correlate with higher financial literacy, higher literacy does not appear to directly drive participation in financial activities. Consequently, the Japanese government may need to consider supplementary or alternative measures to promote the shift from savings to investment. Enhancing confidence in financial literacy could support desirable financial activities, aligning with OECD recommendations that emphasize knowledge alone is insufficient for behavioral change. Additionally, the impact of age on financial activities may relate to perceived relevancy. Although age itself cannot be intervened, initiatives could foster a stronger sense of relevancy to encourage financial planning.

Moreover, our study reveals the complex relationship between financial literacy and financial activities, suggesting the need for dynamic, culturally relevant curricula that integrate real-world financial tools to bridge the gap between knowledge and action. These programs should be updated regularly to reflect emerging research and trends, to improve financial education both in Japan and globally. In addition, the significant influence of Japanese investment strategies on global markets highlights the importance of understanding these dynamics to inform regional policy decisions.

To expand the impact of this research, we propose applying this causal discovery approach to international datasets. This cross-cultural application can provide deeper insights into how financial literacy influences financial activities in diverse cultural and economic contexts. We hope this study encourages further discussions on applying causal discovery algorithms to financial activity survey data. Equally important, we aim for the insights gained here to assist policymakers in Japan and beyond in promoting the financial wellbeing of households.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://doi.org/10.34500/SSJDA.1689.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

YJ: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. SS: Funding acquisition, Methodology, Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This work was partially supported by JST CREST JPMJCR22D2.

Acknowledgments

The data for this study, "Financial Literacy Survey, 2022, (Japan Financial Literacy and Education Corporation)" was provided by the Social Science Japan Data Archive, Center for Social Research and Data Archives, Institute of Social Science, The University of Tokyo.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frbhe.2025.1725333/full#supplementary-material

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