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Examining the Factor Structure of Objective Health Literacy and Numeracy Scales: Large-Scale Cross-Sectional Study

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Abstract

Background: Scales for measuring health literacy and numeracy have been broadly classified into performance-based (objective) and self-reported (subjective) scales. Both types of scales have been widely used in research and practice; however, they are not always consistent and may assess different latent constructs. Furthermore, an increasing number of objective measures have been developed, and it is unclear how many latent factors should be assumed.

Objective: This study aimed to examine the psychometric properties and factor structure of items assessing objective health literacy across multiple scales and to clarify which aspects of objective health literacy would be correlated with subjective measures, as well as health behaviors and lifestyles.

Methods: A total of 5 objective scales (72 items in total) were administered to Japanese-speaking adults (N=16,097; women: 7722/16,097, 48%; mean age 54.89, SD 16.46 years). The analyzed scales included items assessing the numeracy, comprehension, and application of health information, some of which were contextualized for specific diseases, such as diabetes and cancer. Participants' responses were submitted to exploratory factor analysis, and individual factor scores were calculated to test correlations with subjective health literacy, health behavior, and lifestyle.

Results: Exploratory factor analysis identified 3 factors, which were interpreted as conceptual knowledge, numeracy, and synthesis. The conceptual knowledge factor consisted of items about medical word comprehension. All numeracy items loaded onto the same factor, even when contextualized for different diseases. The synthesis factor was characterized by items assessing the ability to read and understand health-related information and make judgments on it using one's own knowledge. The identified factors showed high interfactor correlations (*r* values 0.53 - 0.64) and small-to-moderate correlations with subjective health literacy (*r* values 0.14 - 0.45). Additionally, each factor indicated small positive correlations with healthy diet and nutrition and lower substance use (*r* values 0.17 - 0.26).

Conclusions: Our findings suggest that scales of objective health literacy have at least three latent constructs (ie, conceptual knowledge, numeracy, and synthesis) and that disease specificity is not psychometrically prominent. Each factor has some overlap with subjective health literacy, but overall, subjective and objective health literacy should be interpreted as independent constructs, given the small-to-modest correlations.

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KEYWORDS

objective health literacy; objective health numeracy; health-related behaviors; exploratory factor analysis; confirmatory factor analysis

Introduction

Background

Health literacy plays a pivotal role in acquiring and maintaining healthy lifestyles, which help individuals prevent diseases and maintain their well-being [1]. Although the definition of health literacy varies across studies, the core concept refers to the ability of an individual to obtain, process, understand, and use health information and services [2]. This conceptualization covers health numeracy, namely, applying numerical and quantitative reasoning skills to navigate a health care environment, access care, engage in treatment, and make informed health decisions [3]. Empirical studies have demonstrated that lower health literacy, including lower health numeracy, is associated with lower autonomy and self-control in health behaviors as well as negative health outcomes, such as higher older adult mortality, increased emergency and inpatient facility use, lower medication compliance, and lower preventive service use [3,4].

Health literacy assessment has long been a research target, and hundreds of measures have been developed and published over the past 3 decades [5-8]. As Nguyen [6] noted, a typical assessment approach is to ask respondents to self-report about their experience on Likert scales (ie, subjective measurement), whereas it is also common to challenge individuals using standardized test stimuli to evaluate their underlying traits, knowledge, skills, and numeracy [9-12] (ie, objective measurement). For example, the Lipkus Numeracy Scale (henceforth, Lipkus) requires respondents to perform numeracy tests in general (eg, "Imagine that we rolled a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?") [12]. Another typical approach is to assess word comprehension of health-related and medical terms [13]. It is also common to present responders with hypothetical scenarios or visual materials, such as nutrition labels [14,15] or maps of hospitals [16], to assess their ability to read, interpret, and process relevant information. Objective measures have been suggested to be suitable for estimating individual skills guiding actual health behavior [6]—an experimental study showed that individuals with high levels of objective (but not subjective) health literacy were able to critically evaluate health information on websites, which further helped them to choose an appropriate treatment option [17]. In addition, a prospective cohort study on patients with cardiovascular-related diseases showed that the lack of objective health literacy predicted poor refill adherence [18].

In contrast, most subjective measures ask respondents to self-report their perceptions and experiences of handling health information, typically using a Likert scale [6]. The 47-item European Health Literacy Survey Questionnaire (HLS-EU-Q47) [19] is one of the most widely used measures to assess individuals' perceived abilities to access, understand, appraise, and apply health information (eg, "Finding information on symptoms of illnesses that concern you is..."; respondents indicate from very easy to very difficult) [19]. Another example is the Subjective Numeracy Scale (SNS), which assesses individuals' beliefs about their skill in performing various mathematical operations (eg, "How good are you at working with fractions?") and individuals' preferences regarding the presentation of numerical information (eg, "When reading the newspaper, how helpful do you find tables and graphs that are parts of a story?") [20]. Subjective measures typically assess individuals' self-perceived ability to find and understand health-related information as well as their confidence in doing so [17]. Also, some measures cover a wider range of psychological (eg, motivation and self-efficacy) aspects of health literacy [21]. A study suggested that individuals with lower levels of subjective numeracy are less motivated and less confident in numeric tasks [22]. Furthermore, the European Health Literacy Survey showed that subjective (but not objective) health literacy is predictive of self-perceived health [23], which might suggest that subjective measures may be more suited to studying perception and beliefs about health status and behavior.

The objective and subjective measures appeared to tap into the same latent construct, that is, the ability to process health information. However, Waters et al [24] suggested that these 2 types of measures assess conceptually related but psychometrically distinct constructs and that numeracy should be separated from general health literacy. Begoray and Kwan [25] found almost null correlations between objective (word recognition and reading comprehension) and subjective (self-reporting of skills to access and communicate health information) assessments. Marks et al [26] suggested that objective measures may reflect medication knowledge, whereas subjective measures may not. For the associations with health outcomes and behaviors, a systematic review [27] concluded that the evidence is mixed. Several studies observed no differences between performance-based and self-reported health literacy for the associations with relevant health outcomes (eg, diabetes, stroke, and hypertension), whereas others documented objective-subjective discrepancies (eg, for cancer screening use). Hirsh et al [28] noticed that the self-reported disease severity of rheumatoid arthritis was associated with subjective health literacy but not with objective health literacy, including the ability to read and pronounce medical terms.

The possibility that objective and subjective measures assess different constructs of health literacy may make it difficult for researchers and practitioners to determine which type (or both) to include in their assessment batteries. Another challenge when building an assessment battery for health literacy research is that an enormous number of measures have been developed; thus far, there is no clear guidance on which to use and when [8]. Recently, we conducted an exploratory factor analysis of 219 items across 11 subjective measures (encompassing 45 subscales), indicating that dimension reduction was effective, as the items were well explained by 7 latent factors [29].

Objectives

In this study, we aimed to expand these findings to objective health literacy measures; namely, we conducted an exploratory factor analysis on 5 performance-based measures of health literacy and numeracy (see the *Methods* section for the selection criteria of the analyzed scales), including general and disease-specific (ie, chronic pain, cancer, and diabetes) scales. Through the analyses, we explored how many and what factors would emerge. In addition to the number of factors identified, we were also interested in whether disease-specific items would be recognized as independent factors or factors that reflect common skills and performances regardless of target diseases. Simultaneously, the identified factors were tested for their correlations with lifestyle and health status, as well as subjective health literacy and numeracy, to explore the consistencies and inconsistencies (or validity) with perceived health literacy and behaviors.

Methods

Data

Data from a larger longitudinal survey on the health behaviors, psychological characteristics, and lifestyles of Japanese-speaking adults (aged >18 y living in Japan) were used. We used quota sampling to represent the population distribution for age and gender in Japan, and thus, we did not use a survey weight in the analysis. The overarching project (still ongoing) is a 3-year longitudinal study that includes multiple waves with different focuses: wave 1 (N=20,573; early 2023) for physical activity (PA) and psychological characteristics [30] and for mobile health technology use [31], wave 2 (conducted in 2023; 6 mo after wave 1) for changes in PA and digital health behaviors [32], and wave 3 (conducted in early 2024) for health literacy and lifestyle. Wave 3 included both subjective and objective health literacy scales; the psychometric properties of the subjective scales have been reported elsewhere [26]. This study used the wave 3 data (N=16,097; women: 7722/16,097, 48%; mean age 54.89, SD 16.46 years), of which 87% (14,064/16,097) participated in wave 1. As the dropout rate was high, an additional sample of 2033 participants was recruited at wave 3. This addition was for the overarching project but not for this study specifically. Although we could not use quotas in this extra sampling due to the time pressure that we had, we found that the age and gender distributions were similar to those of the general population, so we included this additional sample in the analysis. This study focused exclusively on objective scales. We used data from 5 objective health literacy (or numeracy) scales together with the validation measures of subjective health literacy, health behavior, and lifestyle (refer to the *Measures* section).

Ethical Considerations

Participants were paid for online panels recruited by a survey firm. Interested individuals followed a link to the survey site, and on the top page, they received study information (written) and provided informed consent to proceed to individual questionnaire pages. Each participant was assigned a study ID, which was used as the key in merging their responses across different waves. No personal information was obtained throughout the study. The study was approved by the Ethics Committee of the National Institute of Advanced Industrial Science and Technology (approval ID: 2022 - 1279).

Measures

Objective Health Literacy and Numeracy Scales

We selected the scales for inclusion in this study following published reviews (eg, [8,33,34], including Tavousi et al [8], the latest review on health literacy scales over the past 3 decades when the study was conceptualized, and Nakadai et al [34], a narrative review of the scales available in Japanese). Among the scales listed, we included those that met the following criteria: the scale was available in English or Japanese and could be implemented on a static online survey (ie, did not require audiovisual materials or in-person interactions), and specific instructions and items were available from published articles, supporting materials, or personal correspondence with the authors of the scales. This selection process resulted in four objective health literacy or numeracy scales: the Lipkus [12,35], Newest Vital Sign (NVS) scale [14,15], Functional Health Literacy Scale for Young Adults (funHLS) [13], and Cancer Health Literacy Test (CHLT) scale [16]. An additional database search (Google Scholar and PubMed) identified the Diabetes Health Numeracy (DHN) scale [36], which was eligible for this study. Table 1 summarizes the characteristics of each included scale; most objective health literacy scales are not Likert type. For example, the funHLS presented medical stem terms (eg, caries) and asked participants to indicate the most relevant words for each stem term among 3 response options (eg, virus, bacteria, and fungus). Across the scales, each response was binary coded to represent 1 (correct) and 0 (incorrect), and the total score was calculated for each scale, with higher values indicating higher levels of objective health literacy or numeracy. It should be noted that the current analyses included translated versions of the scales, and responses to some of the items were potentially affected by cultural differences. For example, the NVS and CHLT included items assessing comprehension of food nutrition and prescription medication labels. These stimuli were modified to be familiar to Japanese respondents—particularly for the NVS, the translation and adjustment were conducted rigorously in accordance with the established cross-cultural adaptation guidelines [37,38].

Table . Overview of the objective health literacy and numeracy scales.

Scale name (abbreviation)	Items, n (Cronbach α)	Test format	Description
Lipkus Numeracy Scale (Lipkus) [12,35]	10 (0.79)	Numeric response questions	Measures the ability to understand and use numeric information, particularly for probability: (eg, "Imagine that we rolled a fair, six-sided die 1,000 times. Of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)")?
Newest Vital Sign (NVS) scale [14,15]	6 (0.63)	Numeric response questions and open-ended questions	Measures comprehension, numeracy, and application and evaluation skills. Responders are presented with a nutrition label of ice cream, from which they are required to extract necessary information for calculation (eg, "If you eat the entire container, how many calories will you eat?") and evaluation (eg, "Pretend that you are allergic to the following substances: penicillin, peanuts, latex gloves, and bee stings. Is it safe for you to eat this ice cream?")
Functional Health Literacy Scale for Young Adults (funHLS) [13]	19 (0.93)	Multiple choice questions	Measures knowledge and comprehension of health-related and medical terms. Responders are presented with stem words, for each of which they are asked to indicate the most relevant among 3 response options (eg, stem=caries: response options=virus, bacteria, and fungus).
Diabetes Health Numeracy (DHN) scale [36]	7 (0.85)	Multiple choice questions	Measures numeracy skills, contextualized for diabetes (eg, "If you walk for about 30 minutes you can burn 100 calories. If you want to burn 150 calories, how long do you have to walk?"). Several items tap into interpretation skills (eg, "read a table about diagnostic criteria for diabetes and indicate the stage of an example patient").
Cancer Health Literacy Test scale (CHLT) [16]	30 (0.85)	Multiple choice questions	Measures knowledge (eg, "Which is the highest in calories and protein? – French fries, cheeseburger, hard-boiled egg"), comprehension skills (eg, "In people who develop oral cancers, 25% of these cases occur in the tongue. Oral cancer occurs in the tongue..."), and their synthesis, contextualized for cancer.

Subjective Health Literacy Scale

The HLS-EU-Q47 [19,39] was used to assess subjective health literacy. The HLS-EU-Q47 and other self-report scales (see below) were used as validation measures to test for correlations with objective health literacy measures. The HLS-EU-Q47 measures 4 information-processing competencies (ie, how easy it is to access, understand, appraise, and apply health information) for 3 health-relevant domains (ie, health care, disease prevention, and health promotion). Participants indicated how applicable each item was to them using a 4-point scale (1=very easy and 4=very difficult). For ease of interpretation, each item was reverse scored, with higher values indicating higher health literacy levels, and the total score was normalized to a range between 0 and 50 using the following formula: (mean−1)×(50/3). This scale has shown good reliability in the current data (Cronbach α=0.97).

Subjective Health Numeracy Scale

The SNS was used to assess subjective health numeracy levels [20]. The SNS measures one's perceived ability to perform mathematical tasks (eg, How good are you at working with fractions?) and preferences for the use of numerical (vs prose) information (eg, When reading the newspaper, how helpful do you find tables and graphs that are parts of a story?). Participants indicated how applicable each item was to them using a 4-point scale (1=not good at all, not helpful at all; 4=very good, very helpful). This scale has shown good reliability in the current data (Cronbach α=0.75).

Physical Activity

The International Physical Activity Questionnaire Short Form [40,41] was used to assess PA levels. Respondents were asked to indicate the number of days and minutes per day spent walking, engaging in moderate-intensity activities, and engaging in vigorous-intensity activities. We did not use sedentary time for the current analyses. The weighted sum of the reported durations was calculated across the 3 activity categories, representing the total PA in the form of metabolic equivalents (METs hours per week). According to the Ministry of Health, Labour and Welfare in Japan, the recommended amount is 23 METs hours per week or higher for adults aged <65 years and 10 METs hours per week for older people [42].

Quality of Life and Health State

Quality of life (QoL) and health status were assessed using the 5-level EuroQol 5-Dimension (EQ-5D) version [43]. Participants indicated their health status by selecting the most appropriate statement (ie, no problems to extreme problems) for the following five dimensions: mobility, self-care, usual activities, pain or discomfort, and anxiety or depression. Participants' responses were combined into a 5-digit code, which was then converted into a numerical QoL score. The QoL score ranges from −0.025 to 1, where a negative value signifies a condition worse than death, 0 represents a state equivalent to death, and 1 denotes the highest possible health utility. At the end of the EQ-5D questions, participants were asked to rate their health status using a visual analog scale, ranging from 0 to 100, with 0 representing the worst health condition they could imagine and 100 representing the best health condition they could imagine.

Health-Related Lifestyles

The Short Multidimensional Inventory Lifestyle Evaluation (SMILE; [44]) consists of 45 items covering seven domains of health-related lifestyles: diet and nutrition, substance use, PA, strategies to deal with stress, sleep pattern, social support, and environmental exposure. Items asking about the use of illegal drugs (ie, items 10 and 11) were excluded to adhere to the ethics standards of the administering survey firm, and the remaining 43 items were used in the survey. Participants rated each item on a 4-point scale (1=always and 4=not at all). Summed scores were calculated for each domain, whereas items were reverse scored (with higher values indicating healthier lifestyles). The global score (sum of the 7 domains) demonstrated good internal consistency in the current data (Cronbach α=0.88).

Statistical Analysis

An exploratory factor analysis was conducted on the 5 objective health literacy and numeracy scales. We excluded from the analysis (1) an item (funHLS12) exhibiting high correlations with other items (r values 0.72 ‑ 0.80) and (2) 5 items to which >90% of participants responded correctly (ie, items 2, 4, 14, and 27 of the CHLT and item 5 of the Lipkus). The final dataset consisted of 66 items. As each item was binary scored (correct vs incorrect), polychoric correlations were calculated and used in factor analysis. The number of factors was determined based on the reduction in eigenvalues (ie, a scree plot), as well as on the interpretability of the identified factors. Exploratory factor analysis was conducted on randomly sampled 70% of the data (n=11,268), and the remaining 30% (n=4829) was used for confirmatory factor analysis as testing data. Before factor analyses, each dataset was tested with the Kaiser-Meyer-Olkin sampling adequacy measure (≥0.8; Kaiser 1970; [45]) and Bartlett sphericity test (P≤.05; [46]). Confirmatory factor analysis was conducted with maximum likelihood estimation to replicate the factor structure obtained in the exploratory factor analysis. Our focus was on the goodness of fit of the model to the data, evaluated by the following indices: chi-square [47], comparative fit index [48], root mean square error of approximation [47,49], and the standardized root mean square residual [47]. For each factor, items with factor loadings of 0.40 or greater (a commonly used threshold for identifying meaningful loadings; eg, see [50]) were interpreted and were used to calculate a factor score (as the mean of raw item scores). For each factor, items with factor loadings of 0.40 or greater were interpreted and were used to calculate a factor score (as the mean of raw item scores). These factor scores were tested for correlations with validation measures (ie, subjective health literacy and numeracy scales, PA, QoL, health status, and health-related lifestyles). All analyses were performed using R (version 4.3.3; R Foundation for Statistical Computing). The *factanal* function was used for the exploratory factor analysis, and the *cfa* function of the *lavaan* package [51] was used for the confirmatory factor analysis.

Results

Descriptive Information

Table 2 presents the descriptive statistics. For the objective measures, the mean scores were comparable to those reported in previous studies—for example, in the general Japanese population (Lipkus, mean 9.6) [35], an Italian population-based sample (NVS, mean 4.1) [52], and a sample from the United States (CHLT, mean 22.3) [16]. The total score on the HLS-EU-Q47 was slightly higher than that reported among Japanese people (mean 25.3) but lower than that reported among Europeans in the literature (mean 33.8) [39].

Table . Descriptive statistics (n=16,097).

Variable	Values
Age (y), mean (SD)	54.89 (16.46)
Gender (women), n (%)	7722 (48)
Objective health literacy and numeracy scales, mean (SD)	
Lipkus[a]	7.80 (2.34)
NVS[b]	3.50 (1.69)
funHLS[c]	14.14 (5.21)
DHN[d]	5.38 (2.09)
CHLT[e]	24.67 (4.89)
Subjective health literacy and numeracy scales, mean (SD)	
HLS-EU-Q47[f]	28.23 (8.07)
SNS[g]	3.24 (0.67)

[a]Lipkus: Lipkus Numeracy Scale.

[b]NVS: Newest Vital Sign scale.

[c]funHLS: Functional Health Literacy Scale for Young Adults.

[d]DHN: Diabetes Health Numeracy scale.

[e]CHLT: Cancer Health Literacy Test scale.

[f]HLS-EU-Q47: 47-item European Health Literacy Survey Questionnaire. A general health literacy index score comprising all items was standardized on a metric between 0 and 50, using the following formula: (mean − 1) × (50/3).

[g]SNS: Subjective Numeracy Scale.

Exploratory Factor Analysis

The factor analysis performed on 66 items across 5 scales revealed eigenvalues of 16.43, 3.09, 1.93, and 1.59 for the 1- to 4-factor solutions. The reduction in the eigenvalue supported the 3-factor solution, with explained variances of 0.16, 0.15, and 0.10 for the 3 factors (total explained variance: 0.41). Additionally, the 3-factor solution had good interpretability; the factor loadings are visualized in Figure 1, which confirms that no items had double or triple loadings. The exact factor loadings for each item are listed in Table S1 in Multimedia Appendix 1. Table 3 summarizes the characteristics of each factor.

Figure 1. Items' factor loadings on each factor. CHLT: Cancer Health Literacy Test scale; DHN: Diabetes Health Numeracy scale; FA: factor; funHLS: Functional Health Literacy Scale for Young Adults; Lipkus: Lipkus Numeracy Scale; NVS: Newest Vital Sign scale.

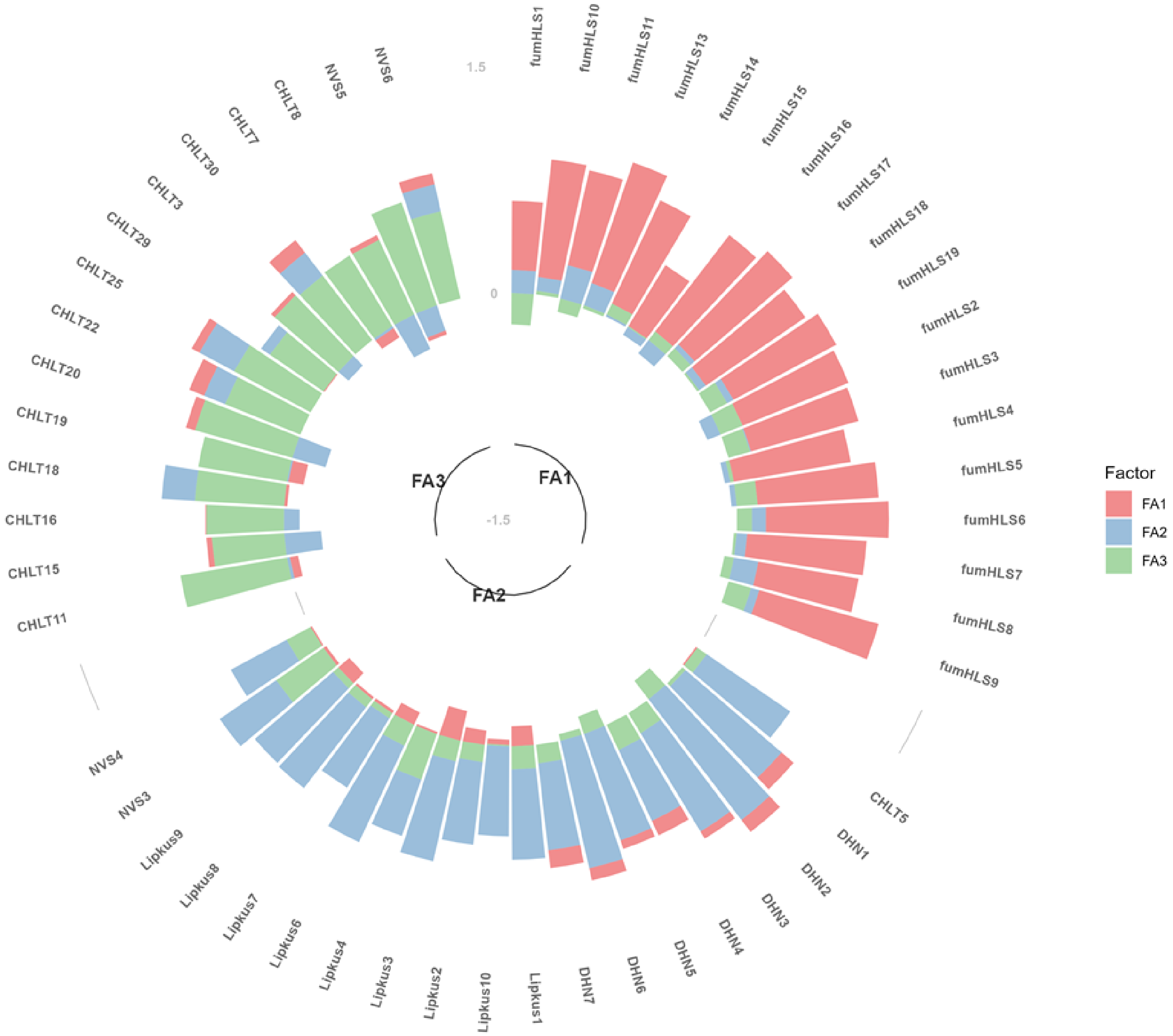

Table . Interpretations of identified factors.

Factor[a] and item with a factor loading of 0.40 or higher	Example item
FA1 (conceptual knowledge)	
funHLS[b] (items 1 - 11 and 13 - 19)	funHLS 6: "Indicate the most relevant word for *Vitamin C.* Response options*: Vegetables, Fat, Grain, and I Don't know.*"
FA2 (numeracy)	
Lipkus[c] (items 1 - 4, 6 - 10)	Lipkus 6: "If Person A's risk of getting a disease is 1% in ten years, and person B's risk is double that of A's, what is B's risk?"
NVS[d] (items 3 and 4)	NVS 3: "Your doctor advises you to reduce the amount of saturated fat in your diet. You usually have 42 g of saturated fat each day, which includes 1 serving of ice cream. If you stop eating ice cream, how many grams of saturated fat would you be consuming each day?"
DHN[e] (items 1 - 7)	DHN 2: "A male diabetic patient weighs 80 kilograms (kg). The doctor advised this patient to lose 10% of his weight. How much weight does this patient need to lose?"
CHLT[f] (item 5)	CHLT 5: "In people who develop oral cancers, 25% of these cases occur in the tongue. Oral cancer occurs in the tongue..."
FA3 (synthesis)	
NVS (items 5 and 6)	NVS 5: "Pretend that you are allergic to the following substances: Penicillin, peanuts, latex gloves, and bee stings. Is it safe for you to eat this ice cream?"
CHLT (items 3, 7 - 8, 11, 15 - 16, 18 - 20, 22, 25, and 29 - 30)	CHLT 18: "An appointment card says not to eat or drink anything 9 hours prior to the appointment. Sally has an appointment at 11:15 a.m. on Friday. What time should she stop eating or drinking?"

[a]The means and SDs of each item as well as their factor loadings are provided in the supplementary materials in Multimedia Appendix 1.

[b]funHLS: Functional Health Literacy Scale for Young Adults.

[c]Lipkus: Lipkus scale.

[d]NVS: Newest Vital Sign scale.

[e]DHN: Diabetes Health Numeracy scale.

[f]CHLT: Cancer Health Literacy Test scale.

Factor 1 (FA1) consisted exclusively of items from the funHLS, which asked participants to indicate the word most relevant to a stem (medical) word. Items from the funHLS assess word comprehension and knowledge about diseases and symptoms that young adults often experience, as well as nutrition, diet, and human biology. All items of the funHLS showed loadings of >0.40 on FA1. Although the funHLS items covered a range of topics (eg, caries, depression, and BMI), most items loaded on the same factor, and items from other scales were not included in FA1. This factor could be interpreted as a conceptual knowledge of health-related and medical terms in general (ie, not limited to a particular disease or health condition); however, it is still possible that the factor may reflect the unique test format, as the other scales require binary (true-false) responses or numeric responses, for example, to calculate a probability or health risk.

Factor 2 (FA2) included items from 4 of the 5 analyzed scales (ie, Lipkus, NVS, DHN, and CHLT), representing performance-based health numeracy in general (eg, "Imagine that we rolled a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up even (2, 4, or 6)?"). These 4 scales target different populations—Lipkus was designed for the general population, whereas the other 3 were contextualized for particular diseases and health conditions (DHN for diabetes and CHLT for cancer). The test format also differed across the 4 scales; the CHLT used multiple-choice questions, whereas the NVS and DHN included numeric response questions. These results suggest that the items assessing performance-based numeracy correlate well with each other, regardless of heterogeneity in the target diseases and test format.

Factor 3 (FA3) included items from 2 scales, the NVS and CHLT, which assess the ability to process and synthesize health-related information. For example, item 5 of the NVS concerns abstract reasoning, integrating reading, comprehending, and interpreting skills as applied to material with health content [15]. Respondents were presented with a hypothetical nutrition label of ice cream and asked to judge whether the ice cream would be safe if the respondents were allergic to the indicated substances. Similarly, many of the items loaded onto FA3 required respondents to comprehend and synthesize the presented information (eg, the nutrition label) to make the correct response. Items from the CHLT are contextualized in a daily cancer patient routine at a clinic (eg, instructions for the use of medicines and reading a floor map of a hospital), assessing respondents' knowledge, numeracy, navigation, and synthesis [16]. Therefore, compared to FA1 (word comprehension and knowledge) and FA2 (numeracy), FA3 is distinguished in that it broadly measures higher order skills that require the synthesis of multiple skills (eg, reading, comprehension, and interpretation) to apply in a daily health context.

Confirmatory Factor Analysis

The testing dataset was found suitable for factor analysis: Kaiser-Meyer-Olkin=0.98 and the Bartlett Test of Sphericity, *P*≤.001. We built a confirmatory factor analysis model with the 3 factors identified through exploratory factor analysis. This model showed an excellent fit to the testing data, χ^2_{1271}=7015.7, comparative fit index=0.97, root mean square error of approximation=0.03, and standardized root mean square residual=0.05, which reassures that the analyzed scales can be reduced to the 3 factors.

Correlation Analysis

The 3 identified factors were tested for their correlations with subjective health literacy and numeracy, as well as with health status and lifestyle (Table 4). Each correlation was interpreted for magnitude but not for statistical significance, given the large sample size of the analyzed dataset. The Cohen guideline was used, with *r*=0.10, 0.30, and 0.50 being interpreted as small, moderate, and large effects, respectively [53,54]. FA1 to FA3 showed large interfactor correlations. However, these factors showed small-to-moderate correlations with the HLS-EU-Q47 (subjective health literacy), SNS (subjective numeracy), and SMILE (subscales of diet, nutrition, and substance use). Moreover, FA1 and FA2 showed small correlations with SMILE sleep and social support (*r* values 0.10 - 0.13). None of the factors showed interpretable size correlations with the International Physical Activity Questionnaire Short Form (total PA) or EQ-5D (QoL and subjective health) scores. The 2 subjective measures, the HLS-EU-Q47 and SNS, presented stronger correlations with the SMILE subscales, except for substance use, than FA1 to FA3.

Table . Correlations between each factor and comprehensive health status.

	Values, mean (SD)	FA1[a]	FA2[b]	FA3[c]	HLS-EU[d]	SNS[e]
FA1	0.74 (0.27)	—[f]	—	—	—	—
FA2	0.75 (0.24)	0.63	—	—	—	—
FA3	0.80 (0.19)	0.53	0.64	—	—	—
HLS-EU-Q47	28.23 (8.07)	0.24	0.19	0.14	—	—
SNS	3.24 (0.67)	0.33	0.45	0.32	—	—
Total physical activity (METs[g] hours per week)	34.20 (55.21)	−0.00	−0.02	−0.05	0.09	0.06
EQ-5D[h] quality of life	0.82 (0.14)	−0.01	0.03	0.02	0.10	0.07
EQ-5D health status	76.17 (17.59)	0.05	0.06	0.02	0.18	0.12
SMILE[i] diet	2.88 (0.49)	0.26	0.24	0.19	0.33	0.27
SMILE substance use	3.29 (0.82)	0.21	0.17	0.20	0.08	0.07
SMILE physical activity	2.29 (0.62)	0.05	0.05	−0.02	0.24	0.19
SMILE stress management	2.40 (0.48)	0.11	0.09	0.02	0.32	0.21
SMILE sleep	2.77 (0.58)	0.10	0.11	0.05	0.23	0.17
SMILE social support	2.59 (0.63)	0.13	0.11	0.06	0.31	0.23
SMILE environment	2.44 (0.53)	0.04	0.03	−0.02	0.16	0.13

[a]FA1: factor 1 (conceptual knowledge).

[b]FA2: factor 2 (numeracy).

[c]FA3: factor 3 (synthesis).

[d]HLS-EU-Q47: 47-item European Health Literacy Survey Questionnaire. A general health literacy index score comprising all items was standardized on a metric between 0 and 50, using the following formula: (mean − 1) × (50/3).

[e]SNS: Subjective Numeracy Scale.

[f]Not available.

[g]MET: metabolic equivalent.

[h]EQ-5L: EuroQol 5-dimension.

[i]SMILE: Short Multidimensional Inventory Lifestyle Evaluation.

Discussion

Principal Findings

This study examined the factor structure of the multiobjective health literacy and numeracy scales among Japanese-speaking adults. Specifically, we explored how many factors would emerge in the pool of 72 items extracted from 5 scales, with or without being contextualized for specific diseases. The exploratory factor analysis indicated that the items could be categorized into three factors: performance-based conceptual knowledge (FA1), numeracy (FA2), and synthesis (FA3).

Most funHLS items loaded on FA1, assessing the conceptual knowledge of health-related and medical terms. FA2 consisted of items from 4 scales targeting people with different health conditions and diseases that typically assess their ability to perform mathematical calculations. The NVS and CHLT items not included in FA1 were identified as FA3, which required the synthesis of multiple skills to handle health information, such as reading, knowledge, navigation, and interpretation skills, to provide a correct response. A correlation analysis indicated that all factors had weak correlations with subjective health literacy, moderate correlations with subjective health numeracy, and weak correlations with lifestyle (eg, diet, nutrition, and substance use). Lifestyles concerning sleep and social support demonstrated small correlations only with FA1 and FA2 but not with FA3.

In line with Altin et al [9] and Wu et al [55], we observed small-to-moderate correlations between the 3 factors and the subjective scales (ie, HLS-EU-Q47 and SNS). Furthermore, the 3 identified factors were highly correlated with each other, yet were recognized as independent factors. These findings echo Waters et al's [24] argument—health literacy and numeracy are related but distinct constructs, each of which can be psychometrically divided into performance-based (objective) and self-reported (subjective) constructs. Another important point is that our analysis did not identify disease-specific factors, although we included cancer- and diabetes-specific items in the item pool. Therefore, it is plausible to assume that the 3 identified factors—conceptual knowledge, numeracy, and synthesis—form a common basis for processing health information in general. Health literacy covers a range of skills from basic to advanced levels. Basic skills include reading and writing (ie, literacy), which allow individuals to function effectively in everyday situations. These skills serve as a foundation for more advanced ones, for example, extracting information, deriving meaning from different sources of communication, and applying new information to changing circumstances [1]. We assume a similar hierarchical structure for the identified 3 factors, which may explain the interfactor correlations; that is, synthesis represents higher order skills that require more basic ones, such as numeracy and knowledge, along with other cognitive and literacy skills (eg, reading, comprehension, and interpretation).

Regarding the associations with health behaviors and lifestyles, each factor presented small correlations with diet and substance use but not with PA. Some overlaps were noticed at the item content level; for example, the NVS includes items about caloric calculation as well as reading and interpreting a nutrition label, whereas the SMILE asks how often respondents eat high-calorie sweet or fatty foods and how frequently they check the food ingredient labels. A similar association was found in patients with diabetes; performance-based numeracy is positively correlated with a healthy diet [56]. These findings suggest that skills and abilities assessed by objective measures underlie perceived health behaviors (eg, individuals are able to read and interpret ingredient labels and check them regularly when shopping for food). However, the size of the correlations was modest, and the results should be interpreted carefully, particularly for the practical significance.

Compared with objective measures, subjective measures demonstrated overall larger correlations with health behaviors and lifestyles. The conceptual knowledge and numeracy factors (FA1 and FA2) had small correlations with sleep and social support of the SMILE (r values 0.11 - 0.13) but subjective health literacy (HLS-EU-Q47) and numeracy (SNS) presented slightly larger correlations with sleep and nutrition (r values 0.17 - 0.33) as well as with other subscales (eg, PA, r=0.24; stress management, r=0.33). Higher levels of objective health literacy are thought to be associated with an inclination to behave in a manner that is beneficial to one's own and others' health (eg, choosing beneficial treatments for a disease) [17]. However, subjective health literacy may share even larger variance with the perception of health behaviors; that is, how people perceive their ability to process health information may overlap with how they believe to behave in a context where their health matters. It is too early to conclude that subjective measures are more suited for studying health behaviors based only on the correlations found in this study. Instead, it is fair to argue that objective and subjective measures reflect different psychological processes, and further research is warranted to clarify which type (or both) of health literacy measure is associated with actual health behaviors that can be assessed using sensors and devices, such as accelerometers for PA.

Limitations

This study has several methodological limitations. First, the item pool was neither exhaustive nor comprehensive. Importantly, we did not include Test of Functional Health Literacy in Adults (TOFHLA) [10] and Rapid Estimate of Adult Literacy in Medicine (REALM) [11], which are the most widely used objective measures, because of language and cultural differences (all materials had to be in the Japanese language) and technical limitations of the survey platform (audio-visual recording could not be implemented). Both tools are closely bound to the English language (or even to the culture and health care system of the country where the scales were developed). For example, the REALM evaluates whether respondents pronounce medical terms correctly, and the TOFHLA assesses the ability to read and understand health-related materials contextualized in the US health care system. Yet, our analyses covered the scales and items conceptually overlapping with the REALM and TOFHLA; the funHLS is a word recognition test for medical terms, the CHLT and NVS assess reading comprehension of texts and tables, and the Lipkus evaluates numerical ability. However, we acknowledge that the exact items of the REALM and TOFHLA were not included here, and this may affect the interpretation of the results, particularly for the generalizability of the study findings. Furthermore, it is highly likely that the results of the factor analysis and subsequent analyses might differ if the item pool were expanded. Second, the exploratory factor analysis showed that the 3-factor structure explained less than half of the total item variance. A possible explanation is that measurement invariance might not be assumed in subgroups of participants as the data covered a diverse range of people in terms of demographics and other psychosocial variables. Different factor structures could be found across participants with different backgrounds, which should be clarified in future research. Third, participants were recruited using quota sampling to match the known population distribution in Japan for age and gender. Quota sampling is useful to ensure broad coverage of different groups and to prevent overrepresentation of a particular group in data. However, this approach is known to be vulnerable to sampling bias within a subgroup, which could be addressed by the use of self-weighted sampling if the cost of random sampling does not matter. Fourth, diagnostic information on physical or mental disorders was not collected. Testing patients with a particular disease or disorder was out of our focus, as we set a community sample as our target population. Health literacy is essential in maintaining one's health and preventing future diseases. However, it is important to widen the focus to include patient care and disease management, for which health literacy and assessments are highly relevant. Fifth, convenient self-reporting tools were used to assess PA and lifestyle habits. Health behaviors can be assessed using wearable devices and e-diaries (eg, food recordings), which may allow for a more reliable estimation of healthy lifestyles [57]. It was technically impossible for us to use device- or sensor-based assessments, given the sample size of this study, but objective assessment tools could be considered when a focused sample is the research target.

Conclusions

Despite these limitations, our findings contribute to the psychometric evidence base of objective health literacy and numeracy scales. The results of the exploratory factor analysis identified 3 factors—conceptual knowledge, numeracy, and synthesis—among 66 items from 5 scales, independent of disease specificity and different contextualizations of the items. These 3 factors showed marginal correlations with subjective measures of health literacy and numeracy, highlighting the distinction between performance-based and self-reported assessment approaches [58]. Researchers and practitioners should be aware that self-report measures do not always reflect the skills and abilities reflected in performance on tests assessing conceptual knowledge, numeracy, and more integrated information processing skills. In other words, both subjective and objective measures should be considered if one wishes to assess different aspects of health literacy. In general, subjective measures are easier to administer and less cognitively demanding [6,7]; also, these measures are more suitable for assessing meta-cognitive, emotional, or motivational aspects of health literacy rather than knowledge and numeracy [22,27]. However, self-reported measures are vulnerable to social desirability and other biases owing to health beliefs [20], which may reduce the accuracy of assessing health information skills [9]. In contrast, objective measures are less affected by response biases [6,17] but may feel like examinations and evoke a sense of shame and stigma. This aspect is particularly relevant for individuals feeling uncomfortable with examinations and not confident in their skills (eg, test anxiety). Also, objective measures often cover a limited, highly contextualized range of skills [6]. Given these advantages and disadvantages, it is not readily possible to uniformly determine the best measures to assess health literacy. It is important for individual researchers to be aware of what aspects of health literacy they want to assess, which then helps them select appropriate scales and items in line with their objectives.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: KT
Data curation: KT, TO
Formal analysis: CM
Methodology: CM, KT, NK
Project administration: K Kimura
Supervision: KT
Writing – original draft: CM
Writing – reviewing & editing: KT, TO, NK, K Katahira, K Kimura
All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
The means and SDs of each item as well as their factor loadings.
[XLSX File, 19 KB - publichealth_v12i1e71701_app1.xlsx]

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Abbreviations

CHLT: Cancer Health Literacy Test
DHN: Diabetes Health Numeracy
EQ-5D: EuroQol 5-Dimension
funHLS: Functional Health Literacy Scale for Young Adults
HLS-EU-Q47: 47-item European Health Literacy Survey Questionnaire
Lipkus: Lipkus Numeracy Scale
MET: metabolic equivalent
NVS: Newest Vital Sign
PA: physical activity
QoL: quality of life
REALM: Rapid Estimate of Adult Literacy in Medicine
SMILE: Short Multidimensional Inventory Lifestyle Evaluation
SNS: Subjective Numeracy Scale
TOFHLA: Test of Functional Health Literacy in Adults

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Original Paper

A Social Media Campaign to Promote COVID-19 Vaccination: Cost-Effectiveness Analysis

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Abstract

Background: Vaccine hesitancy has increased in recent decades internationally, which sets up a critical barrier to the rapid deployment of novel vaccines against infection with SARS-CoV-2.

Objective: This study used a quasi-experimental design to evaluate the cost-effectiveness of a social media intervention to reduce COVID-19 vaccine hesitancy implemented in Nigeria in 2022.

Methods: The intervention targeted health care providers and adults from the general population who were users of a specific social media platform. We used published estimates from a quasi-experimental evaluation of the campaign's effectiveness compared to the status quo across 6 intervention states and 31 comparison states over a 10-month period. We estimated the cost-effectiveness of the campaign in terms of cost (2022 US dollars) per person vaccinated using a decision tree analysis and probabilistic sensitivity analysis.

Results: On the basis of the quasi-experimental trial, the campaign led to a crude 6.4–percentage point increase (219/692, 31.6% vs 117/463, 25.3%; P=.045) in vaccination rates and an adjusted 7.8–percentage point increase (95% CI 1.68-14.2; P=.02) controlling for age group, gender, educational level, religion, and occupation among the 20% (1933/9607) of the overall sample who were unvaccinated and in the persuadable middle. Scaled to the overall population, the campaign led to a 1.57–percentage point (95% CI 0.337-2.87; P=.02) increase in the proportion of those vaccinated against COVID-19 among those reached by the social media campaign. The social media campaign resulted in 58.3 million impressions and 1.87 million people reached for a total societal cost of US $1.15 million, or US $0.61 per person reached. This resulted in an incremental cost-effectiveness ratio of US $54.70 (95% uncertainty interval US $20.90-$163) per person vaccinated.

Conclusions: A social media–based campaign to address COVID-19 vaccine hesitancy in 6 states in Nigeria resulted in an increase in vaccination rates. The cost-effectiveness of the campaign compared to no campaign is comparable to that of other campaigns promoting COVID-19 vaccine uptake. The cost per person vaccinated due to the social media campaign was 1% to 8% of the estimated cost per life year saved by vaccination against COVID-19 in low- and middle-income countries. Investing in social media campaigns would likely be a cost-effective approach to increase vaccine uptake and save lives.

(JMIR Public Health Surveill 2026;12:e84540) doi:10.2196/84540

KEYWORDS

COVID-19; vaccination; social media; cost-effectiveness; health promotion

Introduction

The COVID-19 pandemic led to the death of 15 to 20 million people worldwide up to 2021 [1,2]. In response to this threat, governments and private companies demonstrated high capacity for innovation; the rapid development and testing of multiple effective vaccines stands out as a critical success [3]. The pandemic also highlighted ongoing systemic failures in global and national public health systems, including limited capacity for surveillance, communication, and distribution of preventive materials and services [4]. These failures exacerbated existing health inequities within and between countries.

The potential impact of the successful development, manufacture, and distribution of effective vaccines was not fully realized due to the public health system's inability to communicate the safety and benefit of the new vaccines in the context of widespread mis- and disinformation about the pandemic and the public health response. Building on well-established antivaccine movements, COVID-19 vaccine hesitancy emerged as a major barrier to the control of the pandemic [5]. By November 2023, a total of 80% of people living in high-income countries had received at least one dose of a COVID-19 vaccine compared to 33% of people living in low-income countries [6]. In the years before the COVID-19 pandemic, researchers were evaluating the potential use of social media communication campaigns to address vaccine misinformation and increase vaccine uptake. Previous vaccine promotion campaigns addressing vaccine hesitancy have mostly targeted a narrow set of vaccines (eg, influenza and human papillomavirus in high-income countries and diphtheria, tetanus, pertussis, and polio in middle- and low-income countries) [7]. Reviews of health promotion campaigns covering communicable and noncommunicable diseases on social media have found limited or mixed evidence of reported or observed behavior changes (ie, high engagement) and more reports of interaction with posts or changes in knowledge and attitudes (ie, low to medium engagement) [8,9].

With this promising but mixed and limited research base, and accompanied by calls for development of theoretically based and practice-based social marketing strategies [10], funders and public health organizations rapidly implemented social media campaigns to promote COVID-19 vaccine uptake. Initial evaluations of efforts to promote COVID-19 vaccination or other disease control behaviors through social media campaigns have been positive but with low to moderate effects, leading the public health community to consider whether and how to invest in a sustainable public health social media communication infrastructure [11-14]. Social media campaigns have the potential to reach targeted audiences with tailored messages in ways that may improve both impact and efficiency compared to mass media campaigns [15].

We evaluated the cost-effectiveness of a targeted social media campaign to promote vaccination against COVID-19 among health care providers and other adults in their social environment in Nigeria in 2022. By May 2022, after recording 250,000 COVID-19 cases, Nigeria had received enough COVID-19 vaccines to cover 25% of the population and had administered the first dose to 13% and the second dose to 8% of the population [16]. High levels of vaccine acceptance (76%) in late 2020 were being reported to be much lower as more data were published in 2021 (40%-60%) [16,17]. The World Bank, which classifies Nigeria as a lower-middle–income country, reported that 38% of the Nigerian population accessed the internet in 2022 [18]. A rapid rise in the use of social media in Nigeria and its complex role in the response to COVID-19 had been reported by the time the social media campaign in this paper had been implemented [19].

In this analysis, we aimed to evaluate the cost of implementing a social influencer–based social media campaign and estimate the value of the campaign in terms of cost per person vaccinated, which can be compared to other campaigns targeting vaccine uptake.

Methods

Overview

The prospective economic analysis plan was included in the overall analysis plan submitted to the funder and has not been published elsewhere. This project followed the guidelines of the Second Panel on Cost-Effectiveness in Health and Medicine and the reporting guidelines from the Consolidated Health Economic Evaluation Reporting Standards checklist [20,21]. The data used in the model synthesis were collected from 2021 to 2022. The analysis was completed in 2023.

Intervention Description

This cost-effectiveness analysis is based on the implementation and quasi-experimental evaluation of a 10-month social media campaign promoting vaccination against COVID-19 in Nigeria among health care workers and those in their social networks in 2022 [22]. The campaign was designed and implemented by a team of designers and local organizations and delivered through Facebook and Instagram. The campaign included provaccination social norms and vaccine hesitancy reduction messages delivered by social influencers (eg, local celebrities, health care providers, and religious and business leaders). The campaign theory of change was based on the theory of diffusion of innovations; social norms theory; and the motivation, opportunity, and ability framework [23-25].

Study Population and Setting

The intervention was implemented in 6 states in Nigeria (Anambra, Bauchi, Lagos, Niger, Rivers, and Sokoto), with participants in the control condition recruited from the Federal Capital Territory and all other states. Participants were eligible if they were aged ≥18 years, had a Facebook account registered in Nigeria and received recruitment advertising in their live feed promoting a study on COVID-19 vaccination, had not been previously vaccinated against COVID-19, and were defined as members of the "persuadable middle" [22]. Those who responded “Definitely” or “Definitely not” to the question “Would you take a COVID-19 vaccine that is approved for use in Nigeria if offered to you?” were excluded based on not being in the persuadable middle. While people in low- and middle-income countries (LMICs) generally have higher vaccine acceptance than those in high-income countries. Nigeria faced vaccine availability and other challenges that may have impacted vaccine hesitancy differently than in higher-income settings, including perceptions that safety and efficacy had not been adequately evaluated in that setting [26-28].

Cost Evaluation

We used the standard microcosting approach, for which we evaluated all component costs of the intervention instead of using a global project budget. Microcosting includes 3 main steps: identification, measurement, and valuation. To identify the resources used, we prospectively developed a detailed description of the intervention activities and identified necessary resources for each activity. Resources were measured and valued using actual reported expenditures from implementing partners and reported or estimated opportunity costs for the nonbudgeted time from implementing partners, influencer organizations, and participants. Direct costs were all reported in US dollars by the implementing partners and were adjusted for inflation to 2022 US dollars. Opportunity costs accrued in Nigeria were estimated in 2022 Nigerian naira. Nigerian currency was converted to purchasing power parities, with total costs reported in 2022 purchasing power parities, which is equivalent to 2022 US dollars. Costs were converted in 2023. As we did not assess health or economic benefits of vaccination, we did not include opportunity costs of individuals or direct health care sector costs for receipt of the vaccine.

Intervention Reach

The intervention included 245 distinct advertising campaigns implemented on the Facebook social media platform, which means that the campaigns may have included distinct creative content or audience-targeting and promotion methods and their unique individual reach could not be combined with that of other campaigns. For each of these campaigns, the platform reported the total number of unique individuals receiving campaign messages (reach), the total impressions (ie, the number of times the campaign message was displayed on the target audience member’s screen), and a range of engagement metrics for each of these campaigns. Because we did not have access to the total number of unique individuals reached across all campaigns, we estimated reach based on the largest reported reach across all campaigns. Due to a lack of data on the degree of overlap within a targeted campaign, we based our reach estimate on a conservative assumption that there was complete audience overlap across campaigns.

Cost-Effectiveness Analysis

We used a societal and payer perspective, which captured both the budgetary costs of implementing a similar campaign in the future and the opportunity costs of implementing partners and individuals engaging with campaign messages. The comparator was the status quo (ie, the current state of affairs in the absence of this intervention), which was chosen based on the intervention design and effect estimate. The time horizon for this study was 1 year to capture planning and implementation; we did not have the capacity to model longer-term health and cost effects following a change in vaccination rates. We did not discount costs or benefits over the 1-year time horizon.

Outcome Measurement

The primary outcome for this study was vaccination against COVID-19. The incremental effect of exposure to the advertising campaign was estimated from a survey of 10,965 participants who were users of the Facebook social media platform. Of the initial 10,965 participants screened for eligibility, 6198 (56.5%) were excluded as already vaccinated, 1476 (13.5%) were excluded for not being in the persuadable middle, 675 (6.2%) were excluded for missing baseline data, 648 (5.9%) were excluded for not meeting the age criteria, and 35 (0.3%) were excluded for having a duplicate ID. The remaining 17.6% (1933/10,965) of the participants were enrolled in the study. Surveys were fielded to the same cohort, with baseline data collection taking place during the period from December 1 to 31, 2021; first follow-up data collection taking place during the period from March 1, 2022, to April 30, 2022; and second follow-up data collection taking place during the period from October 1 to 4, 2022. Of the 1933 participants enrolled in the study, 1155 (59.8%) completed the first follow-up, and 462 (23.9%) completed the second follow-up. Exposure was based on state of residence, with the intervention implemented in 6 states (Anambra, Bauchi, Lagos, Niger, Rivers, and Sokoto) and control participants recruited from all other states in Nigeria.

Participants were recruited through a social media–based research platform called Virtual Lab. Recruitment was stratified by whether participants were health care providers, with the goal of recruiting 50% of the sample from the health care provider community. COVID-19 vaccination uptake was measured through a single question: “Have you received a COVID-19 vaccine?” Participants could respond as follows: “Yes, a single-dose vaccine”; “Yes, the first dose of a two-dose regimen”; “Yes, both doses of a two-dose regimen”; and “No.” Due to changes in the types of vaccines available, as well as recommendations for boosters, we collapsed the outcome into a binary “vaccinated or not vaccinated” outcome.

The effect of the intervention was estimated using a linear regression model predicting vaccination status at the midpoint and final survey. The primary independent variable in each model was exposure to the intervention. Adjusted models included the following control variables: age group, gender, educational level, religion, and occupation. We used clustered SEs to account for nesting within state of residence. Additional details on the evaluation of the intervention on vaccine uptake are reported elsewhere [22].

For the purposes of this cost-effectiveness analysis, we estimated the reach of the campaign in the intervention states based on the impressions reported by the Facebook social media platform. Impressions are defined as an individual user’s exposure to specific content on the platform that may or may not result in active engagement, such as liking, commenting, or following the account that disseminated or originated the content [29].

Impressions have been shown to account for most of the information exposure on social media, have low correlation with active engagement or “expression,” and be independently correlated with user-reported influence of a given information source [29].

Uncertainty Analyses

We conducted a probabilistic sensitivity analysis by sampling from the distributions of all parameters with measured uncertainty (Table 1). We included the following scenario analysis: instead of using the effect estimate from the first follow-up from the original outcome study [22], we used the effect estimate from the second follow-up period from the same study. We did not evaluate the heterogeneity of the intervention effect or distributional effects of the intervention. Decision tree models and the probabilistic sensitivity analysis were conducted using TreeAge Pro (R2.0; TreeAge Software, LLC).

Table 1. Summary of inputs for the cost-effectiveness analysis of the COVID-19 vaccine promotion social media campaign in Nigeria in 2022.

Variable	Source	Point estimate (95% uncertainty interval)	Distribution (parameters)
Target population already vaccinated at the start of the campaign (%)	Quasi-experimental trial data [22]	64.5 (63.5 to 65.5)	Binomial (p[a]=0.645, n[a]=9607)
Persuadable middle population among those unvaccinated (%)	Quasi-experimental trial data [22]	56.7 (55.1 to 58.3)	Binomial (p=0.567, n=3409)
Percentage point increase in vaccination status due to treatment among the persuadable middle	Quasi-experimental trial data [22]	7.8 (1.68 to 14.2)	Normal (mean 0.078, SD 0.032)
Campaign reach	Meta advertiser platform	1,870,000	—[b]
Average engagement time per media impression (s)	Publisher analysis [30]	1.7	—
Total campaign impressions	Meta advertiser platform	58,300,000	—
Total cost (US $)	Campaign microcosting	1,150,000	—
Cost per person reached (US $)	Calculation	0.613	—
Sensitivity and scenario analyses			
Scenario 1: percentage point increase in vaccination status due to treatment among the persuadable middle using the second follow-up	Quasi-experimental trial data [22]	11.0 (−0.00337 to 0.225)	Normal (mean 0.110, SD 0.058)

[a]Parameters of each named distribution, where p denotes the probability and n denotes the number of trials.

[b]Not applicable.

Ethical Considerations

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional or national research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards. This evaluation was approved by the George Washington University Institutional Review Board (NCR213708), as well as by the National Health Research Ethics Committee in Nigeria (NHREC/01/01/2007-04/10/2021). No identifiable data were used in this study. All participants provided informed consent to participate in the study following the institutional review board–approved protocol. Participants were compensated with 400 naira (approximately US $1) for completion of the 40-item survey implemented through the Facebook Messenger chat function.

Results

The intervention generated 58,255,000 total impressions across 245 distinct advertising campaigns, which, on the Meta platform (the company that owns Facebook), included one or more sets of individual advertisements. Distinct campaigns were run to allow the intervention to best measure and optimize performance against advertising objectives. The mean reach (unique individuals generating one or more impressions) per campaign was 100,000 (SD 176,000; range 1000-1,873,000). On the basis of an assumption that there was complete overlap across distinct advertising campaigns, the intervention reached 1,873,000 unique individuals.

We summarize intervention costs by activity category in Table 2. Due to the use of marketing labor in the United States and the United Kingdom as well as dollar-denominated contracts with partners in Nigeria, the payer costs accounted for 93% of the total societal costs even though the paid hours to implement the project constituted 14% of the total person-time included in the societal perspective.

Table 2. Cost of the COVID-19 vaccine promotion social media campaign by activity in Nigeria in 2022.[a]

	Payer perspective (US $)	Societal perspective (US $)
Government liaison	73,400	73,400
Monitoring and evaluation	98,300	98,300
Campaign development	360,000	360,000
Advertising expenditure	102,000	102,000
Advertising campaign implementation	134,000	134,000
Stakeholder management	293,000	293,000
Participant engagement with advertising	—[b]	77,700
Influencer campaign implementation	—	7520
Total	1,060,000	1,150,000

[a]Costs may not add up due to rounding.

[b]There are no participant opportunity costs included in the payer perspective.

Across both the control and intervention samples (excluding those who were ineligible based on age, duplicate ID, and missing baseline data), 64.5% (6198/9607) of the participants were already vaccinated at baseline. The vaccination rate among this sample of Facebook users was substantially higher than the 13% single-dose uptake reported at a similar point in the rollout (eg, May 2022) [16]. Of the 3409 participants screened in the study who were not vaccinated and were otherwise eligible, 1933 (56.7%) were considered to be in the persuadable middle and were enrolled in the study. In a previous study, we estimated that the intervention led to a 7.8–percentage point increase (95% CI 1.68-14.2) in vaccine uptake controlling for demographic variables among those in the persuadable middle.

In the primary analysis, we estimated that the incremental cost of the intervention per person reached was US $0.63 and the incremental percentage point increase in vaccination prevalence was 0.0157 (95% uncertainty interval [UI] 0.00337-0.0287). This resulted in an incremental cost-effectiveness ratio of US $54.70 (95% UI US $20.90-$163), which means that it cost US $54.70 more than the status quo (ie, the current state of affairs without the intervention) for every additional vaccination.

In scenario analysis 1, we used the effect estimate from the second follow-up of the same study as the primary analysis. In this scenario, the larger percentage point increase in vaccinations per person (0.0221 vs 0.0157) than in the no-intervention condition reduced the incremental cost-effectiveness ratio almost by half (US $29.60, 95% UI negative to US $180; Table 3). The UI includes 0 due to the smaller sample at the second follow-up and resulting marginally significant coefficient reported in the evaluation study. We found that using this estimate resulted in 3% of all model iterations having a negative effect.

Table 3. Cost-effectiveness results of the COVID-19 vaccine promotion social media campaign in Nigeria in 2022.

	Mean (95% uncertainty interval)
Incremental cost per person reached (US $)	0.613 (0.613 to 0.613)
Incremental increase in COVID-19 vaccinations per person exposed to the campaign	0.0157 (0.00337 to 0.0287)
Incremental cost-effectiveness ratio (US $ per vaccination)	54.70 (20.90 to 163)
Scenario 1: incremental COVID-19 vaccination per person	0.0221 (−0.000649 to 0.0452)[a]
Scenario 1: incremental cost-effectiveness ratio (US $ per vaccination)	29.60 (negative to 180)[b]

[a]For scenario 1, we used an alternative estimate of the effectiveness of the intervention from the second follow-up period of the same intervention used for the primary analysis.

[b]A total of 3% of the model iterations were negative.

Discussion

Principal Findings

In this cost-effectiveness analysis of a social media campaign promoting vaccination against COVID-19 among health care workers and adults in their social environment in Nigeria in 2022, we found that the intervention increased vaccination rates among the target audience at a cost in line with similar efforts in the field.

Incremental cost-effectiveness estimates of media campaigns promoting vaccine uptake vary substantially. On the basis of an analysis of attitude changes as a result of social media campaigns run by 174 public health organizations during the COVID-19 pandemic and another study linking attitudes to vaccination outcomes, Athey et al [31] estimated that the campaigns cost US $5.68 per person vaccinated. The study by Athey et al [31] only incorporated the cost of advertising, which accounted for only 12% of the total costs of running and participating in the campaign in our study. This suggests that our estimate of US $54.70 is likely consistent with that of the analysis by Athey et al [31] (which estimated that it would cost US $48 per person vaccinated assuming a similar cost structure) and highlights the importance of incorporating as many relevant costs as feasible when presenting the cost-effectiveness of social media campaigns.

Because there is no willingness-to-pay threshold for the cost of an incremental person vaccinated, it may be useful to integrate the findings of this study with those of others that have measured the cost per year of life saved (YLS) or cost per disability-adjusted or quality-adjusted life year. A study estimating health benefits and donor costs of increase in COVID-19 vaccination rates in 91 LMICs found that spending on vaccination would cost between US $670 per YLS and US $7820 per YLS depending on the level of vaccination achieved [32]. The authors noted that the cost per YLS for COVID-19 vaccination was similar to the cost for antiretroviral therapy for HIV under the President's Emergency Plan for AIDS Relief, which they estimated at US $4310 per YLS using the total budget and life years saved from the President's Emergency Plan for AIDS Relief 2004 to 2013 [31]. The cost per person vaccinated in this study (US $54.70) was between 1% and 8% of the estimated cost per YLS by vaccination against COVID-19 in the 91 LMICs in the aforementioned study [32]. To further contextualize the value of the social media campaign evaluated in this study, vaccination against COVID-19 in LMICs was estimated to prevent 20.39 deaths per 10,000 people vaccinated; each death from COVID-19 was separately estimated to lead to 16 years of life lost [33,34]. This means that, for each person vaccinated, there was an average of 0.0326 (20.39 × 16/10,000) years of life lost prevented. On the basis of the estimates of the variable cost of vaccination delivery after rollout of a national campaign (US $10 for the vaccine and US $2.46 for delivery) and the cost of promotion obtained from this study (US $54.70), the marginal cost for each vaccination delivered would be US $67.16, leading to an estimate of US $2060 per year of life lost averted. The value of rapidly disseminating science-based vaccine promotion in terms of within-country health benefits likely underestimates the benefits of responding to shared global vulnerabilities with shared investments in mutually beneficial solutions such as vaccination. Baker et al [35] highlight this need for rapid collaboration as they paint an alarming picture of our new era of globally shared infectious disease risk caused by the confluence of climate change, urbanization, migration, travel, and intensifying trade of plants and animals.

Much of the work to prepare and launch this specific campaign to increase COVID-19 vaccine uptake could support other public health communications campaigns in Nigeria and potentially other countries. Moving the intervention to scale, such as all 37 states instead of the 6 in the intervention arm of this study, would spread fixed costs across a much larger population and reduce the cost per person vaccinated substantially. Goulbourne and Yanovitzky [36] argue that the COVID-19 pandemic clarified the role of health communication infrastructure as a social determinant of health and that public health organizations will need to invest in hyperlocal health communication capacity across populations to address health inequities. They suggest that training and providing ongoing technical support to trusted intermediaries is one approach to providing hyperlocal health communication at scale. The intervention evaluated in this study did implement the COVID-19 vaccine promotion social media campaign through 12 local health organizations and 10 other local influencers. The involvement of local influencers to shape and deliver health messages was considered an essential component of the campaign. This approach could limit the degree to which the intervention could be scaled at a lower marginal cost.

A primary limitation of this cost-effectiveness analysis is that we were not able to obtain a specific estimate of the total unique individuals reached by the intervention on the Meta platform. To be conservative, we estimated a total intervention reach of 1.87 million unique users based on the reach of the largest single campaign and not the 24.5 million reached if we summed the reported reach estimates for all campaigns. Our estimated US $0.61 per person reached by the campaign would instead be US $0.05, shifting the cost per vaccination from US $54.70 to US $2.98. This order of magnitude difference in the cost-effectiveness of the intervention emphasizes the importance of understanding how social media reach metrics are reported and how studies estimating the same cost-effectiveness outcomes (eg, cost per person vaccinated against COVID-19) are using these metrics. The lack of comparability across studies may be further compounded when studies only use active engagement or expression as a measure of campaign reach [29].

The extent of competing social media and other communication campaigns promoting vaccination against COVID-19, as well as the high levels of mis- and disinformation about the pandemic and the vaccines on the same social media platforms, created another limitation. The incremental effect of the intervention campaigns on the message environment was lower than it would have been in a nonpandemic context. We were not able to assess any competing or synergistic effects of the campaign due to variation in individual or community media environments, nor were we able to evaluate how the campaign interacted with other public health campaigns on the same platform or across channels. Extrapolation of findings from this study period to future pandemics may be limited by the rapidly changing nature of the social media landscape, including as it relates to platform responsibility to address public health misinformation. The recent divergence in the degree of regulatory control over content moderation between the European Union's Digital Services Act requirement that platforms address the systemic risks posed by misinformation and American jurisprudence's strengthening of free speech protections of content moderation means that mostly American corporations will potentially pursue jurisdictionally fragmented approaches to misinformation during the next pandemic [37].

We used a self-reported measure of vaccination, which could potentially overestimate the effect of the intervention. Stephenson et al [38] reported that, among a sample of approximately 2000 patients with both self-reported and recorded COVID-19 vaccination status in a hospital setting, the self-reported and recorded vaccination status matched for 95% of the participants. While we used existing studies on the cost-effectiveness of vaccination in similar settings [32], we did not directly estimate how the campaign affected health outcomes, which may vary based on, among other factors, the vaccination level in the community, underlying demography and health status of the population, type of vaccine used, and health care system cost and effectiveness. Incorporating these factors within evaluation of new health communication and other strategies is likely infeasible for most interventions but could be accomplished by partnering with modeling groups that do address these factors or through sustained support of modeling consortia that could share modeling capacity more rapidly during future pandemics [39].

Conclusions

We found that a local influencer–based social media campaign implemented in 6 states in Nigeria during the COVID-19 pandemic increased COVID-19 vaccination rates among those exposed to the campaign. The campaign demonstrated comparable cost-effectiveness to that of other COVID-19 vaccination campaigns when accounting for differences in cost data included across studies. When combined with existing estimates of the effect of vaccination against COVID-19 on mortality and years of life lost per death due to COVID-19, this intervention achieved a lower cost per year of life lost averted (US $2060) than debated but recognized thresholds of 3 times the national gross domestic product per year of life lost averted [40]. Boosting the reach of vaccination efforts through influencer-based social media campaigns such as the one implemented in this study is likely to be a cost-effective approach to save lives.

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Data Availability

The datasets generated or analyzed during this study are available from the corresponding author on reasonable request.

Authors' Contributions

Conceptualization: MWL, JBB, and WDE
Data curation: MWL
Formal analysis: MWL
Funding acquisition: WDE
Investigation: MWL, JBB, KN, DD, NR, S Akaba, S Agha, and WDE
Methodology: MWL, JBB, and WDE
Project administration: S Akaba
Supervision: WDE
Writing—original draft: MWL
Writing—review and editing: MWL, JBB, KN, DD, NR, S Akaba, S Agha, and WDE

Conflicts of Interest

NR has ownership interests in Virtual Lab, LLC, a company that uses open-source software described in this paper (Virtual Lab) to provide paid services. S Agha, the project officer, who was an employee of the funder at the time this project was initiated, participated in discussions about the study design and data collection. At the time of this manuscript preparation, S Agha was no longer with the funder. S Agha did participate in the development of the manuscript as noted in the Authors' Contributions section.

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Abbreviations

LMIC: low- or middle-income country
UI: uncertainty interval
YLS: year of life saved

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Developmental Trajectories of Positive Expectancies of Cannabis Use Effects Among Early Adolescents: Longitudinal Observational Study Using Latent Class Growth Analysis

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Abstract

Background: Positive expectancies of cannabis use effects, which are the beliefs about the anticipated positive effects of cannabis, are robust cognitive precursors of adolescent cannabis initiation and escalation. However, little is known about how sociodemographic, familial, and psychopathological factors predict positive expectancies of cannabis use effects or how these expectancies evolve across early adolescence.

Objective: This study aimed to identify distinct developmental trajectories of positive expectancies of cannabis use effects among early adolescents, as well as the longitudinal effects of familial factors on positive expectancies of cannabis use effects over time.

Methods: This study used latent class growth analysis with 3 waves of longitudinal data from the Adolescent Brain Cognitive Development Study (ABCD Study) to identify distinct trajectories of positive expectancies of cannabis use effects among a large, demographically diverse cohort of early adolescents (aged 10 - 13 years). Multinomial logistic regression was used to examine whether baseline sociodemographic and policy-level factors were associated with class membership. Time-varying effects of familial factors (ie, parental monitoring, family cannabis use rules, and family conflict) and adolescents' psychopathology were examined within and across trajectory classes using class-specific and common effects models.

Results: Four distinct trajectories of positive expectancies of cannabis use effects emerged with different profiles: moderate-increasing (3118/7409, 42.1%), high-increasing (2111/7409, 28.5%), low-increasing (1496/7409, 20.2%), and high-decreasing (684/7409, 9.2%) trajectories. Parental monitoring and strict family cannabis use rules consistently predicted lower positive expectancies of cannabis use effects, particularly in the moderate- and high-increasing groups, while family conflict emerged as a robust risk factor. Psychopathological symptoms became increasingly predictive of positive expectancies of cannabis use effects at later ages, suggesting a developmental shift in vulnerability.

Conclusions: The development of positive expectancies of cannabis use effects in early adolescence is heterogeneous and shaped by the interplay among sociodemographic, familial, and psychopathological factors. These findings highlight the critical window for early, family-based prevention and underscore the importance of tailoring intervention strategies to specific developmental and risk profiles.

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KEYWORDS

positive cannabis use expectancy; latent class growth analysis; family dynamics; early adolescents; parental monitoring; family cannabis use rules; family conflict

Introduction

Background

Adolescent cannabis use is a significant public health concern in the United States. Despite its federally illegal status [1], it is estimated that 11.2% (2.9 million) of US adolescents (aged 12 - 17 years) used cannabis during the past 12 months [2]. Prior research has shown that early initiation, frequent use, and escalating cannabis use during adolescence are associated with a range of adverse developmental outcomes, including academic underachievement, impaired social functioning, increased risks for depression and suicidality, elevated likelihood of developing substance use disorders, and poorer psychosocial and occupational functioning in later adulthood [3-6]. Understanding cognitive antecedents of cannabis use, particularly positive expectancies of cannabis use effects, is critical for effective prevention.

Substance use expectancies are beliefs about the anticipated effects of using a particular substance, which can serve as critical proximal cognitive mechanisms determining whether an individual will initiate the use of a substance or continue substance use later in life [7-12]. Furthermore, substance use expectancies serve as a core construct in various psychological theories explaining substance use behavior [13], including social learning theory [14-16]; expectancy theory [17]; and plans, responses, impulses, motives, and evaluations (PRIME) theory [18]. Social learning theory emphasizes that substance-related cognitions are acquired through observational learning, modeling, and reinforcement in salient social contexts, such as the family. Expectancy theory and PRIME theory expand on this by conceptualizing that expectancies form as part of a broader evaluative cognitive network that guides motivation, decision-making, and dynamic behavioral choices, which precedes and organizes actual substance use behavior.

Guided primarily by social learning theory, this study focuses on examining how early adolescents, who are particularly sensitive to familial cues, are likely to form positive expectancies of cannabis use effects in response to familial factors. In this context, defining trajectories of positive expectancies of cannabis use effects and identifying family factors (eg, household rules, parental monitoring, and family conflict) that predict membership in different trajectories of positive expectancies of cannabis use effects are essential for informing early interventions and refining theoretical models of cannabis use during early adolescence.

Positive Expectancies of Cannabis Use Effects

Positive expectancies of cannabis use effects include anticipated feelings of relaxation, enhanced creativity, and social connection when using cannabis [19,20], and have been consistently identified as key cognitive drivers of cannabis use behaviors [21-28]. Adolescents who hold more positive beliefs about the anticipated effects of cannabis use are significantly more likely to initiate cannabis use at an earlier age and engage in sustained and/or escalating use over time, even after controlling for other known established risk factors [29,30]. This underscores the unique etiological role of positive expectancies of cannabis use effects in shaping the developmental trajectories of future cannabis initiation. More importantly, positive expectancies of cannabis use effects are modifiable, making them compelling targets for early interventions, before beliefs become firmly entrenched.

Despite growing concerns surrounding adolescent cannabis use and the need for prevention, research has largely focused on behaviors emerging in late adolescence, often neglecting early adolescence (ages 10 - 14 years), a critical period when expectancies develop before direct cannabis experimentation [31,32]. During this period, there is rapid cognitive, emotional, and social development, and environmental influences play formative roles in shaping substance-related expectancies. Among these, family factors, such as parental monitoring, household rules, and family conflict, are particularly influential as they structure adolescents' early views of substance use [33,34].

Family Influences on Positive Expectancies of Cannabis Use Effects

Family rules regarding substance use, parental monitoring, and family conflict all have robust influences on shaping adolescents' substance-related expectancies but have yet to be examined relative to positive expectancies of cannabis use effects. Substantial research has demonstrated that parental alcohol and tobacco rules influence alcohol and tobacco expectancies and subsequent use [35,36]. Empirical studies focusing on cannabis use have shown that clear, well-defined family rules on cannabis use serve as protective factors for cannabis use, whereas the absence or ambiguity of such rules is linked to increased cannabis use [37]. However, research has yet to examine the influence of family rules on positive expectancies of cannabis use effects. It may be that parents who clearly communicate the risks of substance use and enforce explicit household rules indirectly cultivate lower positive expectancies of cannabis use effects in their children, whereas permissive or neutral parental attitudes on substance use may promote more favorable expectancies about cannabis effects. Notably, findings from broader literature on substance use expectancies may not fully extend to positive expectancies of cannabis use effects. The distinct social, legal, and perceived medicinal aspects of cannabis use may lead adolescents to form unique expectancies that differ from those observed for alcohol or tobacco.

Parental monitoring, defined as active supervision and awareness of adolescents' activities [38], represents another critical protective factor across various domains of adolescent risk behavior. Parental monitoring has been consistently associated with reduced alcohol, cannabis, and nicotine use across diverse demographic groups [39-42]. In addition to deterring actual use behaviors, higher levels of parental monitoring are associated with a lower intention to initiate substance use [43]. Given the demonstrated impact on behavioral intentions and decision-making, higher levels of parental monitoring may also reduce adolescents' positive expectancies of cannabis use effects, although direct empirical evidence remains limited.

Family conflict has been robustly associated with an increased risk of substance use and more favorable expectancies of alcohol use [44-47]. Mechanistically, conflict may undermine parental authority, increase psychological distress, and elicit maladaptive coping strategies, thereby engendering positive attitudes toward substance use [48,49]. While most research has centered on alcohol, the underlying mechanisms are likely applicable to cannabis, warranting extension of these findings to positive expectancies of cannabis use effects. Thus, family rules, parental monitoring, and family conflict represent key proximal determinants of the formation and trajectory of positive expectancies of cannabis use effects. Understanding their dynamics provides important leverage points for targeted interventions that may disrupt adolescent cannabis risk trajectories.

Of note, previous studies on substance use expectancies have relied on conventional growth models to examine developmental trajectories [11,50]. These variable-centered approaches assume that all individuals within a population follow a single average growth trajectory and posit that covariates influencing growth factors affect all individuals uniformly [51]. These variable-centered approaches overlook the possibility of distinct subgroups with divergent developmental pathways, limiting the ability to capture the complexity of early adolescent development [52]. To address this limitation, we used latent class growth analysis (LCGA), a person-centered alternative that classifies individuals into distinct subgroups following similar trajectories, thereby capturing unobserved variation in adolescent development [53,54].

Our Study

In this study, we used LCGA to identify distinct developmental trajectories of positive expectancies of cannabis use effects and examine how parental monitoring, family cannabis use rules, and family conflict are associated with trajectories of positive expectancies of cannabis use effects both within and across trajectory classes while adjusting for demographic characteristics. By integrating a person-centered, longitudinal approach, this study seeks to advance our understanding of how familial factors shape the formation and progression of positive expectancies of cannabis use effects during this critical developmental period.

Methods

Data and Study Sample

The data were drawn from the Adolescent Brain Cognitive Development Study (ABCD Study), the largest ongoing longitudinal investigation of development and health among early adolescents in the United States. Funded by the National Institutes of Health (NIH) and conducted across 21 research sites using a rigorous multistage sampling design, the ABCD Study provides a unique opportunity to understand the factors shaping adolescent development, substance use behaviors, and mental health outcomes [55,56]. Recruitment was carried out between 2016 and 2018 using a systematic school-based sampling approach designed to approximate the demographic composition of the national population of 9- and 10-year-old children [57]. Schools were selected through probability sampling methods stratified by geographic region, race and ethnicity distributions, and socioeconomic characteristics. ABCD Study teams coordinated with school administrators to distribute study information, conduct on-site presentations, and invite families to participate [57]. Additional information regarding study design, methodology, and data accessibility can be found on the study website [58]. The present analysis included data from the 1-year (mean age 10-11 years), 2-year (mean age 11-12 years), and 3-year (mean age 12-13 years) follow-up waves. The 1-year follow-up was designated as baseline (T1), with subsequent waves designated as time 2 (T2) and time 3 (T3) for this study.

Participants who had valid data on the outcome variables at T1 were included, yielding an initial analytic sample of 8841 participants. Between T1 and T2, 418 participants were lost to follow-up, and an additional 606 participants were lost between T2 and T3. Furthermore, 408 cases were excluded due to missing poststratification weights, which are required for population-representative estimates. These exclusions led to a final analytic sample of 7409 participants.

Ethical Considerations

This is a secondary analysis of data collected by the ABCD Study. The ABCD Study was approved by the central Institutional Review Board (IRB) of the University of California, San Diego (IRB# 160091) and by the IRB at each of the 21 participating research sites [59,60]. Written informed consent was obtained from all parents or legal guardians prior to data collection [59,60]. This analysis used the deidentified, publicly available ABCD Study dataset obtained through the NIH Data Hub, and it was deemed exempt from human subject review by the investigators' IRB (Indiana University Bloomington; 2008226356). Participants and families were compensated for the time spent participating in the study, with amounts varying by data collection site.

Measurements

Outcome Variables

Positive Expectancies of Cannabis Use Effects

Positive expectancies of cannabis use effects were assessed using youth self-report on the Marijuana Effect Expectancy Questionnaire-Brief (MEEQ-B) [25]. The items assessed the degree to which adolescents believe that (1) "marijuana helps a person relax and feel less tense," (2) "marijuana helps people get along better with others or feel more romantic," and (3) "marijuana enhances creativity or alters perceptions." The MEEQ-B has been validated among adolescents and young adults, effectively capturing beliefs about the effects of cannabis [61]. Youth responded to 3 positive expectancy questions on a 5-point Likert scale, with higher summed scores (range 3 - 15) reflecting stronger positive expectancies. Internal consistency (Cronbach α) for the positive expectancies of cannabis use effects scale indicated good reliability (α=.77 [T1], .80 [T2], and .83 [T3]).

Predictor Variables

Family Cannabis Use Rules

Aligning with previous studies [62-64], cannabis use rules were measured using parental report on the following question: "What are the family rules about using marijuana for your son/daughter?" [65-68] Responses were dichotomized as "strict rules" ("not allowed to use marijuana under any circumstances") versus "lenient/no rules," which included all other responses (ie, "not allowed to use marijuana in the home but no rules outside the home," "allowed to use marijuana in the home with permission," "allowed to use marijuana in the home whenever desired," "no rules set about marijuana use," and "have not yet made rules about my child's marijuana use"). Given our study's focus on cannabis and the high correlation of family rules regarding cannabis, alcohol, and nicotine use (r>0.70), alcohol- and nicotine-specific rules were excluded from the present analyses to minimize multicollinearity and improve model interpretability.

Parental Monitoring

Parental monitoring was assessed using youth self-report on 4 items measured on a 5-point Likert scale (1=Never, 2=Almost never, 3=Sometimes, 4=Often, and 5=Always or almost always), with higher mean scores (range 1 - 5) indicating greater parental knowledge, involvement, oversight, and communication [69]. The four items were as follows: (1) "How often do your parents/guardians know where you are?" (2) "If you are at home while your parents or guardians are away, how often do you know how to contact them?" (3) "How often do you talk to your parents or guardians about your plans for the following day, such as school activities or other engagements?" and (4) "How many times do you and your parents/guardians eat dinner together?" This measure reflects the widely used conceptualization of parental monitoring in adolescent development research [40,70-72].

Family Conflict

Consistent with previous studies using the ABCD Study dataset for developmental research [47,72-74], family conflict was assessed using youth self-report on 9 items from the Family Conflict Subscale of the ABCD Study Parent Family Environment Scale, adapted from the PhenX toolkit [75]. Items were coded as True=1 and False=0, with reverse coding applied to positively worded items. The following items were included: "We fight a lot in our family" (1=True), "Family members sometimes get so angry they throw things" (1=True), "Family members often criticize each other" (1=True), and "Family members sometimes hit each other" (1=True). Reverse-coded items included statements such as "Family members rarely become openly angry" (1=False), "Family members hardly ever lose their tempers" (1=False), "If there's a disagreement in our family, we try hard to smooth things over and keep the peace" (1=False), and "In our family, we believe you don't ever get anywhere by raising your voice" (1=False). The items were averaged together, with higher mean scores indicating greater conflict (range 0 - 9). Internal consistency values (Cronbach α) for this study were .67 (T1), .64 (T2), and .68 (T3).

Covariates

Psychopathology

Consistent with previous studies [76-79], youth psychopathology was assessed with parent-reported standardized total scores from the Child Behavior Checklist (CBCL) [80]. This questionnaire comprises 112 items rated on a 3-point Likert scale (0=Not at all true, 1=Somewhat true, and 2=Very true). The total t scores were adjusted for age and sex norms derived from population studies, ensuring comparability across participants [79]. Higher t scores reflect more severe psychopathological problems (range 24 - 88). Cronbach α was .95 for each time point.

Demographic Covariates

Demographic covariates included participant age (in years), biological sex assigned at birth (male/female), parent-reported race and ethnicity, and parental highest education and household income [40,55,73,74,81]. Following the ABCD Study–provided race-ethnicity variable and established frameworks developed by sociocultural literature using the ABCD Study [73,82], parent-reported youth race and ethnicity were categorized as Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic Asian, and non-Hispanic other/mixed race (including youth whose parents selected multiple racial categories or "Other race") [83]. Parental education was dichotomized as high school or less versus some college or higher, and household income was dichotomized as less than US $75,000 versus US $75,000 or higher [84-86].

State Recreational Cannabis Legalization Status

State recreational cannabis legalization status was coded as legal (Yes) or not legal (No) by the ABCD Study administration based on the participant's state of residence at baseline in the ABCD Study (approximately 1 year before study T1). Because the dataset does not include time-varying recreational cannabis use policy indicators, this baseline measure served as a proxy for legalization status at T1 (study reference time point).

Statistical Analysis

For the descriptive analysis, unweighted frequencies and weighted proportions were assessed for categorical variables, and weighted means with SDs were calculated for continuous variables at each time point. Differences across time points were evaluated using weighted chi-square tests for categorical variables and weighted ANOVA for continuous variables. Prior to modeling the latent growth models, a bivariate correlation matrix was examined to assess multicollinearity between predictors.

A series of latent growth models was fitted to examine developmental trajectories of positive expectancies of cannabis use effects. Unconditional latent growth curve models (LGCMs) were first examined to assess within-person change and determine whether sufficient heterogeneity existed to justify latent class modeling [50,87,88]. Both linear and quadratic LGCMs were tested using maximum likelihood estimation with robust SEs.

Subsequently, LCGA models were used to identify distinct subgroups of adolescents with similar trajectories of positive expectancies of cannabis use effects. Consistent with standard practice, all the LCGA models were specified with intercept and slope variances fixed to zero and residual variances constrained to equality across time points [54]. Unconditional LCGA models with 1 to 7 classes were evaluated to assess the optimal number of trajectory classes. Model fit was assessed using multiple criteria: Akaike information criterion (AIC), Bayesian information criterion (BIC), sample size–adjusted Bayesian information criterion (aBIC), entropy, and Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-aLRT) [89-91]. The optimal model was defined as having the lowest information criterion values, significant LMR-aLRT, entropy ≥0.80, and no class size smaller than 5% of the total sample, which was considered statistically unstable [52].

After determining the best-fitting model, R3STEP (auxiliary procedure that implements the 3-step method for adding predictors of latent class membership specified by Mplus) was applied to examine associations between class membership and time-invariant covariates (ie, age, biological sex, race/ethnicity, parental education, recreational cannabis legal status, and total family income). This procedure accounts for the uncertainty in class assignments by incorporating posterior probabilities into auxiliary multinomial logistic regressions. This approach improves estimation accuracy and protects against biased parameter estimates [92,93]. Race/ethnicity was specified as a nominal variable in Mplus, which dummy-coded the variable using non-Hispanic White as the reference category. Mplus then reported the overall omnibus effect of the race/ethnicity block rather than separate coefficients for each category unless individual dummy-coded contrasts produced statistically separable estimates across class comparisons. The full set of dummy contrasts nevertheless contributed internally to the estimation of the classification error–adjusted multinomial logistic model.

To further explore predictive associations with time-varying variables (ie, family cannabis rules, parental monitoring, family conflict, and psychopathology), 2 complementary models were estimated. A class-specific effects model was used to assess the different effects of time-varying predictors across latent classes without interfering with the predefined trajectory classes. This approach revealed heterogeneity in the associations between time-varying predictors and outcome variables across developmental trajectories. As a sensitivity analysis, a common effects model was used to estimate population-average associations between the time-varying predictors and outcome variables under the assumption that the effects of the time-varying predictors on the outcome variables are homogeneous across all latent classes. This model provides insights to understand the general exposure effects that are consistent across subpopulations.

All LCGA models were estimated using Mplus 8.11 [94]. To ensure model stability and reduce the risk of convergence on the local maxima, a multistage estimation procedure was used. Each model was initialized with 1000 random sets of starting values, from which the 250 best-fitting solutions were retained for final optimization. To further verify solution stability, log-likelihood values were required to replicate across 20 iterations. Likelihood ratio tests (eg, LMR-aLRT) were conducted with an additional set of 1000 random start replications, with 200 used for preliminary evaluation and 500 selected for final optimization, repeated 100 times, to ensure the reliability of model comparison results. Missing data of predictors were imputed using the nonparametric random forest–based approach, which has been shown to perform well in retaining nonlinear relationships and interactions among variables in mixed-type datasets [95]. Descriptive statistics were conducted with R 4.5.0 (via RStudio, Posit). The reporting of this study followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines (Checklist 1) [96].

Results

Descriptive Statistics

Table 1 presents the descriptive statistics of the study sample across the 3 time points. The positive expectancies of cannabis use effects score measured among the participants demonstrated an increasing trend (T1: mean 6.41, SD 2.85; T2: mean 7.20, SD 2.93; T3: mean 7.96, SD 2.99; *P*<.001). Similarly, the proportion of strict family cannabis use rules increased over time from 97.9% (T1) to 98.9% (T3) (*P*<.001). Moreover, family conflict scores increased from 1.90 (SD 1.88) to 2.09 (SD 1.96) (*P*<.001). Parental monitoring scores showed a slight decrease across waves (T1: mean 4.51, SD 0.45; T3: mean 4.38, SD 0.50; *P*<.001).

Table . Descriptive statistics of participants from time 1 to time 3 in the Adolescent Brain Cognitive Development Study (ABCD Study) (N=7409).

Variable[a]	Time 1 (age 10-11 years)[b]	Time 2 (age 11-12 years)[b]	Time 3 (age 12-13 years)[b]	*P* value[c]
Positive expectancies of cannabis use effects (range 3-15), mean (SD)	6.41 (2.85)	7.20 (2.93)	7.96 (2.99)	<.001
Biological sex, n (%)				—
Male	4040 (49.0)	—[d]	—	
Female	3369 (51.0)	—	—	
Race/ethnicity, n (%)				—
NH[e] White	4126 (20.7)	—	—	
NH Black	918 (37.6)	—	—	
Hispanic	1421 (28.9)	—	—	
NH Asian	144 (0.4)	—	—	
NH others	800 (12.3)	—	—	
Parental education, n (%)				—
High school or less	1163 (21.5)	—	—	
Some college or higher	6221 (78.5)	—	—	
Recreational cannabis legal status[f], n (%)				—
No	5114 (72.8)	—	—	
Yes	1973 (27.2)	—	—	
Total family income, n (%)				—
Less than US $75,000	2647 (74.4)	—	—	
US $75,000 or higher	4269 (25.6)	—	—	
Age (range 7 - 16 years), mean (SD)	10.55 (0.64)	11.56 (0.71)	12.51 (0.68)	<.001
Standardized psychopathology *t* score (range 24-88), mean (SD)	45.67 (11.06)	45.11 (11.13)	45.01 (11.25)	<.001
Family conflict score (range 0 - 9), mean (SD)	1.90 (1.88)	1.90 (1.84)	2.09 (1.96)	<.001
Parental monitoring score (range 1 - 5), mean (SD)	4.51 (0.45)	4.50 (0.46)	4.38 (0.50)	<.001
Family cannabis use rules, n (%)				<.001
Lenient/no rules	1685 (2.3)	1331 (1.8)	1010 (1.1)	
Strict rules	5712 (97.9)	6033 (98.2)	6207 (98.9)	

[a]Except for the baseline sociodemographic characteristics (biological sex, race/ethnicity, parental education, and recreational cannabis legal status), all other variables were measured repeatedly from time 1 (T1) to time 3 (T3).

[b]Values represent unweighted frequencies and weighted proportions for categorical variables, and weighted means with SDs for continuous variables. Frequencies may not sum to the total sample size due to missing data.

[c]*P* values were generated using weighted ANOVA for continuous variables and weighted chi-square tests for categorical variables to test differences across waves.

[d]Not applicable.

[e]NH: non-Hispanic.

[f]The cannabis recreational legal status was determined based on the participant's state of residence at the time of their baseline interview in the ABCD Study, which is approximately 1 year prior to T1 in this study.

Unconditional LCGA Model Statistics Regarding Positive Expectancies of Cannabis Use Effects

Table 2 presents the latent class model fit comparisons of the optimal class solutions, ranging from 1 class to 7 classes. Table 3 presents the sizes of the individual classes. While models with a greater number of classes (5-class to 7-class trajectory solutions) were explored, they yielded subgroups with minimal representation (ie, group size <5% of the total sample), raising concerns about model overfitting and limited interpretability.

Table . Latent class model fit comparisons for unconditional latent class growth analysis models regarding positive expectancies of cannabis use effects.

Trajectory (model)	Log likelihood	BIC[a]	aBIC[b]	AIC[c]	LMR-aLRT[d] *P* value	BLRT[e] *P* value	Entropy[f]	Minimal class membership[g] (%)
1 class	−55350.179	110744.910	110729.021	110710.358	—[h]	—	—	—
2 classes	−53156.244	106383.722	106358.349	106328.488	<.001	<.001	0.734	38.9
3 classes	−52609.740	105317.495	105282.540	105241.480	<.001	<.001	0.776	16.9
4 classes[i]	−52116.646	104358.038	104313.549	104261.292	<.001	<.001	0.827	9.2
5 classes	−51746.873	103645.224	103591.202	103527.746	<.001	<.001	0.841	4.4
6 classes	−51583.031	103344.270	103280.714	103206.061	<.001	<.001	0.838	2.9
7 classes	−51396.675	102998.291	102925.202	102839.351	<.001	<.001	0.866	0.4

[a]BIC: Bayesian information criterion.

[b]aBIC: sample size–adjusted Bayesian information criterion.

[c]AIC: Akaike information criterion.

[d]LMR-aLRT: Lo-Mendell-Rubin adjusted likelihood ratio test; *P* value for k-1 refers to a significant improvement in model fit between the class (k) and the preceding class (k-1), which compares whether a profile solution with k profiles fits significantly better than a profile.

[e]BLRT: parametric bootstrapped likelihood ratio test, which is similar to the LMR-aLRT; *P* value refers to a significant improvement in model fit between the class (k) and the preceding class (k-1).

[f]Entropy indicates classification accuracy, with a higher value indicating better classification (range 0-1).

[g]Minimal class membership represents the proportion of participants in the latent class with the smallest membership.

[h]Not applicable.

[i]Selected model.

Table . Sizes of the classes (N=7409).

Trajectory (model)	Class[a]						
	Class 1, n (%)	Class 2, n (%)	Class 3, n (%)	Class 4, n (%)	Class 5, n (%)	Class 6, n (%)	Class 7, n (%)
1 class	7409 (100.0)	—[b]	—	—	—	—	—
2 classes	4530 (61.1)	2879 (38.9)	—	—	—	—	—
3 classes	4125 (55.7)	2035 (27.5)	1249 (16.9)	—	—	—	—
4 classes[c]	2111 (28.5)	684 (9.2)	1496 (20.2)	3118 (42.1)	—	—	—
5 classes	1897 (25.6)	328 (4.4)	3054 (41.2)	1470 (19.8)	660 (8.9)	—	—
6 classes	1864 (25.2)	674 (9.1)	502 (6.8)	1375 (18.6)	2774 (37.4)	220 (2.9)	—
7 classes	1247 (16.8)	31 (0.4)	1439 (19.4)	219 (2.9)	1433 (19.3)	2398 (32.4)	642 (8.7)

[a]Each cell displays the frequency and corresponding proportion of individuals within each latent class. Frequencies represent the unweighted counts, while proportions are calculated relative to the total number within each class or group.

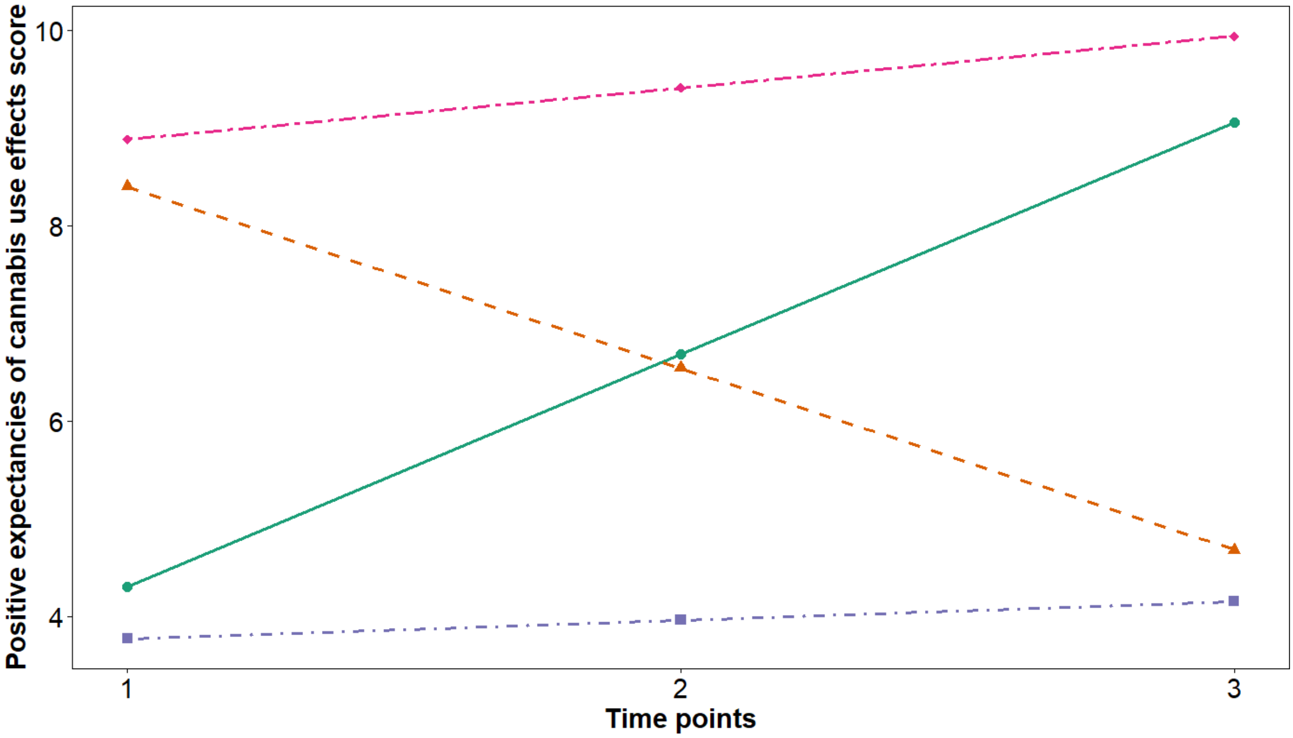
[b]Not applicable.

[c]Selected model.

The 4-class model was selected as the optimal solution based on both statistical fitness and conceptual interpretability. This model demonstrated comparatively lower values for the BIC, aBIC, and AIC and higher entropy compared with the 3-class model, indicating improved classification precision. Compared with the 5-class model, it maintained a balanced class distribution, with each subgroup exceeding the recommended 5% minimum threshold (the smallest group being class 2, with 684 cases or 9.2% of the total sample). Therefore, the 4-class solution balanced parsimony with meaningful subgroup differentiation, which avoided interpretive challenges posed by extremely small latent classes observed in higher-order models.

Figure 1 visualizes the 4-class trajectories. The largest subgroup followed a moderate-increasing trajectory that was characterized by a high baseline level but a moderate increasing trend over time (class 4: moderate-increasing class; n=3118, 42.1% of the sample). The second most prevalent trajectory followed a high-increasing trajectory that was characterized by a moderate baseline level and a steep increase across the study period (class 1: high-increasing class; n=2111, 28.5% of the sample). The third most prevalent trajectory followed a low-increasing trajectory that was characterized by a low baseline level with a slight increase (class 3: low-increasing class; n=1496, 20.2% of the sample). The smallest group followed a high-decreasing trajectory that was characterized by a high baseline level that declined sharply (class 2: high-decreasing class; n=684, 9.2% of the sample). Parameter estimates and detailed trajectory features are reported in Table S3 in Multimedia Appendix 1.

Figure 1. The 4-class developmental trajectories of positive expectancies of cannabis use effects at 3 time points. The y-axis represents the mean positive expectancies of cannabis use effects score, and the x-axis represents the 3 examined time points. The 4 trajectories represent latent classes identified through latent class growth modeling: class 1 is plotted with a solid green line and filled circle markers (2111/7409, 28.5%), class 2 is plotted with an orange dashed line and filled triangle markers (684/7409, 9.2%), class 3 is plotted with a purple dot-dash line and filled square markers (1496/7409, 20.2%), and class 4 is plotted with a pink 2-dash line and filled diamond markers (3118/7409, 42.1%).



Associations Between Baseline Time Invariant Variables and Latent Class Membership

Table 4 presents the results of multinomial logistic regression with the low-increasing class (class 3) serving as the reference category. Compared with this group, youth in the high- and moderate-increasing classes were older (adjusted odds ratio [aOR] 1.13, 95% CI 1.01 - 1.25; *P*=.04 and aOR 1.45, 95% CI 1.31 - 1.60; *P*<.001, respectively). Those in the moderate-increasing class were also more likely to reside in states with legalized recreational cannabis use and be from higher-income families. Multinomial logistic regression findings with other groups as reference categories are reported in Tables S5 - S7 in Multimedia Appendix 1.

Table . Multinomial logistic regression predicting latent class membership (reference class: class 3).

Class[a] and variable[b]	aOR[c,d] (95% CI)	*P* value
Class 1		
Biological sex	0.94 (0.82 - 1.08)	.39
Race/ethnicity	1.03 (0.98 - 1.08)	.27
Parental education	1.06 (0.88 - 1.28)	.53
Recreational cannabis legal status	1.13 (0.96 - 1.32)	.16
Age	1.13 (1.01 - 1.25)	.04[e]
Total family income	1.00 (0.87 - 1.16)	.97
Class 2		
Biological sex	1.05 (0.88 - 1.27)	.59
Race/ethnicity	0.97 (0.90 - 1.04)	.40
Parental education	0.85 (0.67 - 1.09)	.17
Recreational cannabis legal status	1.06 (0.85 - 1.32)	.60
Age	0.99 (0.85 - 1.14)	.88
Total family income	1.09 (0.90 - 1.32)	.40
Class 4		
Biological sex	1.01 (0.89 - 1.15)	.84
Race/ethnicity	1.02 (0.97 - 1.07)	.38
Parental education	0.99 (0.83 - 1.17)	.88
Recreational cannabis legal status	1.28 (1.11 - 1.49)	.003[f]
Age	1.45 (1.31 - 1.60)	<.001[g]
Total family income	1.25 (1.09 - 1.42)	.004[f]

[a]The reference category for this model is class 3 (low-increasing), which represents 1496 participants (20.2%).

[b]For covariates, the reference groups are as follows: female for biological sex, non-Hispanic White for race/ethnicity, high school education or less for parental education, non-legalized status for recreational cannabis legal status, and total family income below US $75,000 for family income. Race/ethnicity was specified as a 5-category nominal covariate and was dummy-coded internally by Mplus. Mplus reports a single omnibus effect representing the overall effect of this multicategory covariate.

[c]aOR: adjusted odds ratio.

[d]Reported odds ratios represent the relative odds of belonging to each latent class versus the reference class for each covariate category.

[e]*P*<.05.

[f]*P*<.01.

[g]*P*<.001.

Dynamic Associations of Family Environment and Psychopathology With the Trajectories of Positive Expectancies of Cannabis Use Effects Within Each Latent Trajectory Class

Table 5 presents the results from the class-specific effects model estimating the time-varying associations of familial and psychopathological predictors with positive expectancies of cannabis use effects across the 4 identified latent trajectory classes. Each class was modeled independently to capture heterogeneity in relation to the predictors over time. Distinct time-varying familial and psychopathological predictors emerged, underscoring differential developmental processes. In the high-increasing class, lower parental monitoring predicted greater expectancy growth at both T1 (β=−0.152, SE=0.072; *P*=.04) and T2 (β=−0.477, SE=0.122; *P*<.001), while increased family conflict at T3 (β=0.071, SE=0.019; *P*<.001) predicted elevated positive expectancies of cannabis use effects. In the high-decreasing class, only family conflict at T2 (β=0.124, SE=0.063; *P*=.047) was a significant risk factor, possibly reflecting transient reinforcement of positive expectancies before decline. The low-increasing class exhibited no significant associations across time points, though family conflict at T3 approached significance (β=0.038, SE=0.021; *P*=.07). In contrast, the moderate-increasing class (the largest group) showed the most consistent effects: less strict family cannabis use rules were significantly associated with expectancy increases at T1 (β=−0.171, SE=0.063; *P*=.006) and T2 (β=−0.212, SE=0.091; *P*=.02), lower parental monitoring was significant at both T2 (β=−0.275, SE=0.088; *P*=.002) and T3 (β=−0.307, SE=0.066; *P*<.001), and family conflict was the most robust predictor from T1 to T3 (*P*<.005).

Table . Class-specific estimates of time-varying predictors of positive expectancies of cannabis use effects across 3 time points.

Class, time, and variable[a]	β	SE	z-statistics	*P* value
Class 1 (high-increasing trajectory)				
Time 1				
Family cannabis use rules	−0.079	0.071	−1.108	.27
Parental monitoring	−0.152	0.072	−2.111	.04[b]
Psychopathology *t* score	−0.004	0.003	−1.293	.20
Family conflict	−0.016	0.017	−0.959	.34
Time 2				
Family cannabis use rules	−0.226	0.149	−1.519	.13
Parental monitoring	−0.477	0.122	−3.922	<.001[c]
Psychopathology *t* score	−0.008	0.006	−1.312	.19
Family conflict	0.019	0.033	0.587	.56
Time 3				
Family cannabis use rules	0.023	0.099	0.229	.82
Parental monitoring	−0.123	0.077	−1.603	.11
Psychopathology *t* score	0.005	0.004	1.527	.13
Family conflict	0.071	0.019	3.687	<.001[c]
Class 2 (high-decreasing trajectory)				
Time 1				
Family cannabis use rules	−0.143	0.141	−1.009	.31
Parental monitoring	0.048	0.139	0.349	.73
Psychopathology *t* score	−0.004	0.006	−0.765	.44
Family conflict	−0.007	0.037	−0.195	.85
Time 2				
Family cannabis use rules	0.150	0.275	0.544	.59
Parental monitoring	−0.369	0.267	−1.381	.17
Psychopathology *t* score	−0.006	0.010	−0.620	.54
Family conflict	0.124	0.063	1.982	.047[b]
Time 3				
Family cannabis use rules	−0.123	0.169	−0.729	.47
Parental monitoring	−0.135	0.129	−1.044	.30
Psychopathology *t* score	−0.010	0.006	−1.825	.07
Family conflict	0.050	0.033	1.500	.13
Class 3 (low-increasing trajectory)				
Time 1				
Family cannabis use rules	−0.065	0.073	−0.886	.38
Parental monitoring	−0.063	0.064	−0.978	.33
Psychopathology *t* score	0.004	0.003	1.408	.16
Family conflict	0.013	0.017	0.801	.42
Time 2				
Family cannabis use rules	0.099	0.150	0.661	.51
Parental monitoring	−0.143	0.119	−1.204	.23

Class, time, and variable[a]	β	SE	z-statistics	*P* value
Psychopathology *t* score	0.002	0.005	0.410	.68
Family conflict	0.040	0.036	1.111	.27
Time 3				
Family cannabis use rules	0.074	0.107	0.697	.49
Parental monitoring	−0.045	0.069	−0.645	.52
Psychopathology *t* score	−0.002	0.003	−0.814	.42
Family conflict	0.038	0.021	1.805	.07
Class 4 (moderate-increasing trajectory)				
Time 1				
Family cannabis use rules	−0.171	0.063	−2.733	.006[d]
Parental monitoring	−0.089	0.068	−1.317	.19
Psychopathology *t* score	0.004	0.003	1.555	.12
Family conflict	0.046	0.016	2.859	.004[d]
Time 2				
Family cannabis use rules	−0.212	0.091	−2.317	.02[b]
Parental monitoring	−0.275	0.088	−3.105	.002[d]
Psychopathology *t* score	0.012	0.004	2.908	.004[d]
Family conflict	0.079	0.022	3.689	<.001[c]
Time 3				
Family cannabis use rules	0.031	0.078	0.402	.69
Parental monitoring	−0.307	0.066	−4.654	<.001[c]
Psychopathology *t* score	0.010	0.003	3.085	.002[d]
Family conflict	0.074	0.016	4.661	<.001[c]

[a]The outcome variable is the individual's level of positive expectancies of cannabis use effects at each time point (time 1, time 2, and time 3) within each latent class. All covariates are repeated measures within respondents from time 1 to time 3. This model does not predict the growth trajectory, but instead, it estimates how time-varying predictors are associated with variation in the positive expectancies of cannabis use effects score over time within each trajectory class.

[b]*P*<.05.

[c]*P*<.001.

[d]*P*<.01.

Shared Associations of Family Environment and Psychopathology With Positive Expectancies of Cannabis Use Effects Across Latent Trajectory Classes

Results from the common effects model are presented in Table S8 in Multimedia Appendix 1, where time-varying familial and psychopathological predictors were constrained to have equal influence across all latent trajectory classes. Strict family cannabis use rules were significantly associated with lower positive expectancies of cannabis use effects at T1 only (β=−0.130, SE=0.040; *P*=.001). However, parental monitoring remained a significant predictor for positive expectancies of cannabis use effects across all 3 time points (T1: β=−0.089, SE=0.040; *P*=.03; T2: β=−0.315, SE=0.061; *P*<.001; T3: β=−0.185, SE=0.040; *P*<.001). Family conflict was a consistent and robust risk factor, with its influence increasing from T2 to T3 (*P*<.001).

Discussion

Heterogeneous Trajectories of Positive Expectancies of Cannabis Use Effects in Early Adolescence

To the best of our knowledge, this is the first study to use a large-scale longitudinal dataset to examine the developmental trajectories of positive expectancies of cannabis use effects in early adolescents, using a person-centered analytic framework. By modeling the development of positive expectancies of cannabis use effects across early adolescence, this study offers novel insights into the dynamic, heterogeneous nature of the formation of positive expectancies of cannabis use effects during this sensitive developmental phase. It identified the following

4 distinct trajectories of positive expectancies of cannabis use effects: high-increasing, high-decreasing, low-increasing, and moderate-increasing trajectories. These trajectories highlight the substantial variability in both the baseline levels and patterns of change in positive expectancies of cannabis use effects, underscoring early adolescence as an important period for tailoring interventions to prevent cannabis use.

Although weighted descriptive statistics across the sample indicated relatively modest population-level changes over the 3 waves, this pattern is expected given the narrow but critical developmental window of early adolescence (approximately ages 11‐13 years) represented in our sample from the ABCD Study cohort. During this period, many psychosocial and contextual characteristics exhibit relative stability at the population level [97], yet substantial *within-person* variability persists in cognitive-affective processes such as substance-related expectancies, social-emotional development, and dynamic familial factors [7,98-100]. LCGA, a person-centered approach, is uniquely suited to capturing individual-level heterogeneity because it identifies subgroups of youth who share similar developmental trajectories even when the overall mean trend appears relatively flat. Accordingly, the 4 trajectory classes identified in this study represent distinct and meaningful expectancy development over time rather than simple cross-sectional differences based on average levels [52,101]. In addition, although the trajectory classes are derived from repeated measures of positive expectancies of cannabis use effects, the LCGA analytic framework used in this study helps minimize potential bias arising from factors, such as parental monitoring and family conflict, which may influence both the development of positive expectancies of cannabis use effects and the predictors included in the R3STEP model. LCGA does not stratify individuals on a single observed positive expectancies of cannabis use effects score; instead, it forms subgroups based on model-estimated posterior probabilities that reflect the overall pattern of trajectories. Moreover, R3STEP estimates covariate associations only after class formation and incorporates adjustment for classification uncertainty, reducing the bias that can arise when treating uncertain class assignments as if they are certain [92]. Within this framework, associations between predictors and class membership represent correlational patterns among latent developmental pathways rather than artifacts of the analytic strategy. Thus, the heterogeneity observed across classes reflects meaningful differences in expectancy development over time, highlighting the advantage of mixture modeling for uncovering nuanced developmental processes that would remain obscure in traditional variable-centered analyses.

Using this approach, the largest trajectory class identified in this study was the moderate-increasing trajectory, which was characterized by relatively high initial levels of positive expectancies of cannabis use effects that increased steadily with time, suggesting an active expectancy formation phase. This pattern may reflect normative developmental processes in early adolescence, where adolescents increasingly seek self-identity and autonomy, and become increasingly susceptible to substance use opportunities [102]. Multivariable comparisons revealed that youth in this trajectory were more likely to be older, from high-income families, and living in states with recreational cannabis legalization. Notably, the consistently elevated and gradually intensifying positive expectancies of cannabis use effects observed in this group are concerning, as the findings point to a sustained expectancy formation process that may heighten the risk for future initiation and persistent use. Youth in this trajectory may be actively shaping their cognitive belief around cannabis use prior to engaging in cannabis use, which may be reinforced by their developmental maturity (older age) and the legal status of recreational cannabis use in their environment. These findings suggest that prevention efforts should extend beyond traditionally high-risk youth to include those on seemingly normative developmental pathways who may nonetheless be building pro-cannabis expectancies that increase long-term vulnerability. The other 3 trajectories provide further insights into heterogeneity in the development of positive expectancies of cannabis use effects, highlighting the substantial variability in both the onset and developmental course of positive expectancies of cannabis use effects and pointing to multiple pathways of risk and resilience in early cannabis-related cognitions.

Familial Protective and Risk Factors

Findings from the common effects model showed that stricter family cannabis use rules and higher levels of parental monitoring were protective against positive expectancies of cannabis use effects during early adolescence. These effects were the strongest at earlier ages, particularly at 10‐11 years (T1) and 11‐12 years (T2). Parental monitoring demonstrated a consistent inverse association with positive expectancies of cannabis use effects across all 3 time points, with the strongest effect at ages 11‐12 years. In contrast, cannabis-specific rules were significant only at T1, with diminished predictive value at later time points. These protective effects align with the findings of a large body of developmental research emphasizing the critical role of structured and engaged parenting in deterring adolescent substance-related cognitions and behaviors [43,103].

The early and pronounced influence of family cannabis use rules underscores their importance in shaping adolescents' cognitive attitudes regarding substance use when they are most embedded within the family context and are more receptive to parental expectations and boundaries [104]. These rules function as clear behavioral norms, potentially counterbalancing early exposure to peer influences and emerging social scripts around cannabis. Although the direct statistical effect weakened by ages 11‐12 years, such rules may establish enduring internalized norms that persist even when external risks are present. Prior research suggests that early parental rule-setting exerts long-term influence on substance-related decision-making. For example, the authoritative parenting style is characterized by setting limits and is linked to lower substance use and less positive attitudes toward drugs throughout adolescence [105-107].

Parental monitoring demonstrated a more enduring and stable protective effect across the developmental period studied. Unlike rule-setting, monitoring reflects an ongoing dynamic engagement with the daily lives of adolescents, which provides not only behavioral oversight but also emotional attunement and accountability [108]. This form of proactive parenting has been consistently shown to reduce adolescents' opportunities to engage in risk behaviors and to shape substance-related cognitions in a protective direction [65,108]. The heightened impact observed at ages 11-12 years may indicate a critical developmental "sweet spot," when adolescents begin to seek autonomy but remain highly responsive to external regulation and support. These findings emphasize the importance of initiating family-based prevention efforts during early adolescence, leveraging this window to reinforce cognitive resistance to substance use before peer norms and societal influences exert stronger effects.

Family conflict emerged as a robust risk factor for elevated positive expectancies of cannabis use effects at ages 12-13 years (T3). In addition, class-specific models showed that this effect was the strongest in the moderate- and high-increasing classes, suggesting that sustained family tensions may accelerate the formation of positive expectancies of cannabis use effects, particularly when not offset by protective parenting practices. This finding is consistent with the findings of a substantial body of literature linking family dysfunction to increased vulnerability to substance use [109,110]. Chronic conflict may erode emotional regulation capacities and model maladaptive coping strategies, thereby reinforcing cannabis as a perceived tool for managing stress [111]. These findings highlight the dual importance of reinforcing protective parenting practices and reducing family conflict during this critical developmental period.

Class-Specific Nuances

Unlike the common effects model, which assumes that predictors operate uniformly across all trajectories, the class-specific model allows the effects of parental and familial factors to vary by trajectory and captures heterogeneity in developmental processes. The findings revealed notable differences in the influences of familial and psychopathological factors across the 4 trajectories of positive expectancies of cannabis use effects.

Parental monitoring was pronounced among adolescents who followed trajectories marked by moderate- and high-increasing risk, where higher monitoring during early and mid-adolescence (ages 10 - 12 years) was associated with significantly lower positive expectancies of cannabis use effects. Additionally, stricter family cannabis use rules were associated with lower positive expectancies of cannabis use effects in the moderate-increasing group at ages 10-11 and 11-12 years. These effects were most pronounced prior to the age of 13 years, underscoring a sensitive developmental window when parental guidance may shape substance-related cognitions before peer norms and autonomy-seeking dominate [112,113]. It is also possible that elevated parental monitoring reflects a reactive process, wherein parents increase oversight in response to perceiving their child's heightened risk or early signs of problematic behaviors. In this interpretation, monitoring may serve as a preventive and responsive strategy, suggesting that parents who recognize vulnerability may intensify supervision as a preemptive measure against further risk escalation.

However, these protective effects were less evident or absent in the high-decreasing and low-increasing trajectories. In the high-decreasing group, early high levels of positive expectancies of cannabis use effects declined over time, and neither parental monitoring nor rule-setting was significantly associated with these shifts. This may suggest that reductions in positive expectancies of cannabis use effects were driven by other factors, such as experiential disconfirmation or broader contextual influences, and further research is warranted for this group of youth. In the low-increasing group, neither monitoring nor rule-setting showed significant associations, though family conflict emerged as a marginal risk factor at later ages. The absence of early effects in this group could reflect other protective dispositional factors (eg, low sensation-seeking) or structural buffers (eg, strong school engagement) not captured in our analysis.

Family conflict emerged as the most robust and class-differentiating risk factor across trajectories, particularly for those at elevated or increasing risk. Adolescents in the moderate- and high-increasing groups exhibited significantly elevated positive expectancies of cannabis use effects in association with greater family conflict, especially by ages 12-13 years. This pattern suggests that interpersonal stress within the home may amplify the development of positive expectancies of cannabis use effects during a period of heightened social and emotional reactivity. In line with developmental cascade models [114], chronic exposure to family conflict may erode previously adaptive cognitive trajectories and accelerate the adoption of risk-promoting beliefs. Conflict was also a significant predictor in the high-decreasing group at mid-stage (ages 11-12 years), suggesting a contemporaneous, level-shifting effect of conflict rather than a change in growth rate. In contrast, conflict showed no impact among adolescents in the low-increasing class, potentially reflecting greater resilience or the presence of unmeasured compensatory mechanisms, such as school connectedness and temperamentally based self-regulation.

Psychopathological symptoms played a more nuanced, temporally specific role. Across most trajectories, they were not significant predictors in early adolescence but became increasingly relevant by ages 11-12 and 12-13 years in the moderate-increasing class. This shift may reflect the growing salience of emotional distress in early adolescence, when academic, social, and identity-related demands intensify, and cannabis may be perceived as a coping tool.

Collectively, several effects were close to statistical significance based on the *P* value. It is likely that we detected small effects because of our large sample size. Therefore, the findings warrant replication.

Limitations

Several limitations should be considered when interpreting the findings of this study. First, the analysis was limited to 3 waves of data collected during early adolescence, which restricts the ability to capture the full developmental trajectory of positive expectancies of cannabis use effects into middle and late adolescence. Given that substance-related attitudes and behaviors often intensify during these later periods, future research with a longer follow-up is needed to determine whether the identified trajectories persist, shift, or predict distal actual cannabis use behavior. Second, the measure of recreational cannabis legalization status was based on state-level policy 1 year prior to this study's baseline (T1) assessment. While useful as a contextual marker, this static measure may not fully reflect the evolving influence of recreational legalization over time, particularly as policy implementation and social norms continue to change. Third, this study used a 3-step LCGA in which covariates and predictors were deliberately excluded from the trajectory formation process and incorporated only in the R3STEP multinomial logistic regression and subsequent class-specific and common effects models. While this approach preserves the integrity of class estimation, unmeasured or imperfectly measured factors may still be associated with both the trajectory of positive expectancies of cannabis use effects and class membership, introducing the possibility of residual confounding. Fourth, the study was unable to account for a range of other social and contextual influences that are becoming increasingly relevant to adolescent development and substance-related behaviors. Given emerging evidence that cannabis-related content on social media can shape adolescents' attitudes, expectancies, and perceived norms, future studies should integrate time-matched assessments of digital media exposure to provide a more comprehensive understanding of expectancy formation.

Public Health Implications

This study fills a critical gap in the literature by identifying 4 distinct developmental trajectories of positive expectancies of cannabis use effects among early adolescents, underscoring the need for prevention strategies that extend beyond universal, one-size-fits-all models. While universal prevention remains important, interventions must be tailored to the heterogeneous developmental pathways identified in this study.

In addition to these practical implications, the observed trajectory patterns and associated family predictors contribute to the development of the current theory. The identification of distinct developmental trajectories of positive expectancies of cannabis use effects suggests that expectancy formation during early adolescence may be heterogeneous rather than uniformly increasing. The findings that stricter household rules and higher parental monitoring were associated with membership in lower or declining classes of positive expectancies of cannabis use effects and that greater family conflict was associated with higher-risk classes of positive expectancies of cannabis use effects are consistent with the social learning theory that emphasizes the role of family environments in shaping evaluative beliefs and related motivational states. Together, these findings suggest that theoretical models of adolescent cannabis use may benefit from incorporating heterogeneity in the development of positive expectancies of cannabis use effects and accounting for the structuring influence of family dynamics during this critical developmental period.

Parental monitoring and clear cannabis use rules were most protective in early adolescence, particularly between the ages of 10 and 12 years, when parental influence remains salient. Intervening during this sensitive period may delay or suppress the rise in positive expectancies of cannabis use effects before peer norms and autonomy-seeking behaviors exert greater influences. These practices are especially critical for adolescents in moderate- and high-increasing trajectories, where sustained parental engagement may disrupt escalation in expectancies. In contrast, family conflict emerged as a robust risk factor, particularly in the later stages of early adolescence. Chronic conflict may amplify cognitive vulnerability, destabilize otherwise adaptive trajectories, and accelerate the internalization of risk-promoting beliefs. Prevention programs that educate parents about conflict management and communication skills could therefore provide meaningful protection. Psychopathology also became increasingly salient by ages 11-13 years, reinforcing the importance of integrated prevention that includes mental health screening and timely intervention. Addressing emotional distress and teaching adaptive coping strategies may reduce the perceived utility of cannabis for managing stress.

Collectively, these findings highlight the value of early, sustained, and nuanced family involvement across developmental stages. Cannabis use prevention programs should also focus on enhancing parental self-efficacy by providing practical tools for effective communication, conflict resolution, and the implementation of developmentally appropriate cannabis use rules [115]. Early adolescence is a critical period during which parental authority still has a dominant influence, particularly for adolescents not yet embedded in high-risk trajectories. For these adolescents, clear and consistent rule-setting within a supportive context may help prevent escalation in expectancies and delay susceptibility.

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Data Availability

Data for this study were derived from the Adolescent Brain Cognitive Development Study (ABCD Study) 5.1 release [118]. Deidentified ABCD Study data are available to qualified investigators through the National Institutes of Health Brain Development Cohorts (NBDC) Data Hub. Information on data access procedures is provided on the ABCD Study data sharing page [119]. The raw data of this study are available on the National Institute of Mental Health Data Archive (NDA) website [120]. Instructions on how to create an NDA study are available on the NDA website [121].

Authors' Contributions

Conceptualization: WAQ, KKE
Data curation: WAQ, SH
Formal analysis: WAQ
Methodology: WAQ, DCS, WJ, SH, KKE
Project administration: WAQ, KKE
Resources: KKE
Software: WAQ, KKE
Supervision: WJ, SH, KKE
Validation: DCS, WJ, SH, KKE
Writing – original draft: WAQ, WJ, KKE
Writing – review & editing: WAQ, DCS, WJ, SH, KKE

Conflicts of Interest

None declared.

Multimedia Appendix 1
Additional data to support the findings of the study.
[DOCX File, 70 KB - publichealth_v12i1e85652_app1.docx]

Checklist 1
STROBE checklist.
[PDF File, 164 KB - publichealth_v12i1e85652_app2.pdf]

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Abbreviations

ABCD Study: Adolescent Brain Cognitive Development Study
aBIC: sample size–adjusted Bayesian information criterion
AIC: Akaike information criterion
aOR: adjusted odds ratio
BIC: Bayesian information criterion
IRB: Institutional Review Board
LCGA: latent class growth analysis
LGCM: latent growth curve model
LMR-aLRT: Lo-Mendell-Rubin adjusted likelihood ratio test
MEEQ-B: Marijuana Effect Expectancy Questionnaire-Brief
NIH: National Institutes of Health
PRIME: plans, responses, impulses, motives, and evaluations

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