

Article

Designing Personal Carbon Accounts for Low-Carbon Consumption: Evidence from a Discrete Choice Experiment in Southwest China

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Abstract

Personal carbon accounts translate everyday low-carbon actions into records, feedback, and rewards, yet there is limited evidence on how users value specific design features. This study examines young adults' preferences for five attributes of personal carbon accounts: tangible welfare incentives, non-material incentives, carbon-reduction rankings, privacy protection, and overall time cost. A discrete choice experiment was conducted with 623 valid respondents in the Sichuan-Chongqing region, and preferences were estimated using conditional logit, mixed logit, and latent class models. Product discounts and ranking feedback increased the relative attractiveness of an account scheme, whereas higher time costs reduced it. Financial credit benefits, personal honorary titles, and public-welfare contributions were less attractive than their respective baseline levels. Blockchain-labeled protection had no significant average advantage over standard anonymization, although responses to this label varied across respondents and latent classes. Preference heterogeneity was concentrated mainly in the valuation of welfare and non-material incentives. These findings suggest that youth-oriented personal carbon accounts should offer benefits that are easy to understand and redeem, provide visible but low-burden feedback, and explain data-protection arrangements in concrete terms.

Keywords: personal carbon accounts; young adults; discrete choice experiment; preference heterogeneity; latent class model; carbon inclusion

1. Introduction

Demand-side mitigation has become increasingly important as climate policy moves beyond production and energy supply. Household consumption generates substantial direct and indirect emissions through energy use, transport, food, housing, and everyday goods [1,2]. The IPCC Sixth Assessment Report and recent mitigation research show that changes in consumption and lifestyles can deliver sizeable emission reductions without necessarily reducing well-being [3–5]. Unlike production-side measures, however, consumer-side mitigation depends on repeated individual decisions. This has renewed interest in personal carbon governance instruments that record low-carbon actions and connect them to feedback or benefits [6–8].

China's carbon-inclusion initiatives have created a particularly active setting for such instruments. Personal carbon accounts, carbon points, and green-consumption rewards



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are now used to connect daily behavior with public-service, market, and financial benefits [9–12]. Ant Forest and local carbon-inclusion platforms show the reach of gamification, social interaction, and point redemption [13,14]. Experience with personal carbon trading and allowance schemes nevertheless indicates that participation depends on fairness, transaction costs, feedback, and institutional trust, not simply on the environmental objective of the program [15–17]. Chinese pilots face similar difficulties, including fragmented accounting standards, weak point credibility, privacy concerns, and a gap between registration and continued use [18,19]. The practical question is therefore no longer whether a personal carbon account can be launched, but how it should be designed so that residents find it worth using.

Young adults are central to this design problem. They are familiar with mobile payments, platform rewards, point redemption, and digital feedback, but digital familiarity does not remove the gap between environmental concern and everyday behavior. Surveys report high levels of climate awareness among young people, while also showing that stated concern does not consistently translate into sustained low-carbon action [20,21]. Research on pro-environmental behavior attributes this gap to behavioral costs, social norms, situational constraints, and perceived control [22–26]. For personal carbon accounts, the relevant issue is therefore not only whether young adults approve of low-carbon goals, but how they evaluate the benefits, feedback, privacy arrangements, and effort required by a specific account scheme [27,28].

Existing studies have examined low-carbon consumption intentions, willingness to pay green premiums, participation in carbon-inclusion programs, and adoption of digital platforms [29]. Much less is known about how users weigh several account attributes at the same time. This omission matters because a scheme that offers an attractive reward may still be rejected if its redemption process is cumbersome, its feedback is unconvincing, or its data practices are unclear. A discrete choice experiment makes these trade-offs observable within a common decision setting.

The empirical analysis addresses three questions: which personal carbon account attributes are most attractive to young adults in the Sichuan-Chongqing region; how users trade off welfare benefits, non-material incentives, ranking feedback, privacy protection, and time cost; and whether these trade-offs vary with financial literacy, environmental attitudes, and subjective environmental knowledge.

The study uses a discrete choice experiment with five account attributes. Conditional logit estimates describe average preferences, the mixed logit model captures continuous preference dispersion, and the latent class model identifies groups with distinct preference structures.

The paper brings account design, China's carbon-inclusion setting, and heterogeneity among young users into a single analytical framework. It links specific attributes to incentive, social-feedback, privacy, and participation-cost mechanisms rather than treating participation intention as a single outcome. It also distinguishes voluntary, platform-based accounts from quota and trading systems that dominate much of the international literature. The resulting evidence is intended to inform the design of youth-oriented accounts without extending stated-choice results to actual long-term use.

2. Literature Review and Theoretical Framework

2.1. Personal Carbon Accounts and Carbon Inclusion in Low-Carbon Development

Personal carbon accounts record individual low-carbon actions and connect them to feedback or benefits. Their policy value lies not in record-keeping alone, but in making otherwise dispersed actions, such as low-carbon travel, recycling, green consumption, and household energy saving, visible within a common account [6,7,30]. Once recorded, these

actions can be linked to points, rewards, progress feedback, and redemption opportunities across different consumption settings.

The institutional form of these accounts varies. They may be linked to carbon labels, public transport, green finance, local carbon-inclusion platforms, or green-consumption programs [31–33]. Research on personal carbon trading and allowances shows that public acceptance depends on how rules allocate costs and benefits, whether participation is convenient, and whether institutions are regarded as fair and trustworthy [6–8,15,16,34]. These findings shift attention from the technical possibility of individual carbon accounting to the design choices through which an account becomes usable and credible.

In China, personal carbon accounts have developed mainly within digital carbon-inclusion programs. Ant Forest, local platforms, and green-finance accounts combine platform data with point redemption, public-welfare activities, and social feedback [9,13,14,18,35]. Their expansion has also exposed unresolved problems: accounting standards differ across platforms, data interfaces remain fragmented, rewards may be difficult to redeem, and the authorization and use of behavioral data are not always clear [9,18,35–37]. These are design problems as much as governance problems because users encounter them through the specific rules and functions of the account.

The literature therefore suggests a narrower question than whether personal carbon accounts are institutionally feasible. What matters for use is whether the account offers benefits that users understand, feedback that they regard as meaningful, privacy arrangements they trust, and participation requirements they consider manageable. Evidence on information, feedback, and transaction costs supports this shift from broad policy feasibility to attribute-level design [38,39].

2.2. Theoretical Mechanisms Underlying Account-Design Preferences

The five experimental attributes are treated as parts of one decision rather than as independent features. The theory of planned behavior provides the broad premise that favorable attitudes do not by themselves produce action when perceived control and contextual constraints are weak [26]. Incentive theory, social-norm research, privacy calculus, and technology-acceptance research then clarify how particular account features can alter the utility of a scheme.

Incentive theory and behavioral economics draw attention to the timing, certainty, and accessibility of rewards [40,41]. Tangible benefits can shorten the perceived distance between a low-carbon action and its personal return, whereas delayed benefits, high redemption thresholds, and complicated rules can reduce perceived value. Account-based rewards may also spill over into other low-carbon behaviors when points, feedback, and consumption settings are closely connected [42]. The likely effect therefore depends on the form of the reward, not merely on whether an incentive is offered.

Social feedback works through a different channel. Peer comparison and visible performance information make low-carbon behavior socially observable and can alter energy and environmental behavior [43–45]. A ranking may provide an immediate reference point, whereas honorary titles or public-welfare contributions rely more heavily on identification with a moral or collective goal. Their value is likely to depend on whether recognition and environmental outcomes are credible and verifiable [46]. Evidence from Chinese digital platforms likewise points to the role of gamification and social interaction in sustaining participation [13,14].

Privacy calculus concerns the exchange between account benefits and the risks of disclosing travel, consumption, and other behavioral data. Users' responses depend on transparency, control over data, perceived risk, and trust in the platform [47–50]. A technical label is therefore not equivalent to perceived protection. Blockchain or other traceability

mechanisms can influence preference only through what users believe the label means for authorization, use boundaries, withdrawal, and oversight. This distinction is particularly relevant to digital carbon-inclusion platforms, where data rights remain an important governance issue [36].

Participation cost completes the framework. Registration, authorization, behavior recording, carbon accounting, and redemption all require time and attention. Technology-acceptance and innovation-diffusion research predicts that complexity can offset the value of otherwise attractive benefits [51,52]. Account preferences should consequently be estimated from combinations of rewards, feedback, privacy arrangements, and effort rather than inferred from environmental attitudes alone. Table 1 summarizes the theoretical link between each mechanism and its corresponding DCE attribute.

Table 1. Theoretical mechanisms, corresponding DCE attributes, and expected effects.

Theoretical Perspective	Mechanism	Corresponding DCE Attribute	Expected Effect
Incentive theory/behavioral economics [40,41,46]	Immediate and low-threshold rewards increase perceived utility	Tangible welfare incentives	Product discounts are expected to be more attractive than delayed or complex financialized benefits
Social norm theory [43–45]	Peer comparison and visible feedback strengthen motivation	Carbon-reduction ranking	Ranking feedback is expected to increase scheme attractiveness
Value-expression/prosocial motivation [25,46]	Moral identity and public contribution support symbolic motivation	Honorary titles, public welfare contribution	Non-material incentives are expected to work when credible and verifiable
Privacy calculus [47–50]	Users weigh account benefits against data-disclosure risks	Privacy protection	Privacy protection is expected to increase attractiveness when the mechanism is understood and trusted
Technology acceptance/diffusion of innovations [51,52]	Perceived ease of use and complexity shape adoption	Overall time cost	Higher time cost is expected to reduce attractiveness
Theory of planned behavior [26]	Attitudes, norms, and perceived control jointly shape intention	Moderators: attitudes, knowledge, literacy	Individual characteristics are expected to moderate attribute preferences

2.3. Research Gap and Analytical Focus

Recent studies establish the broader policy relevance of low-carbon development and carbon inclusion. Low-carbon city policies can improve ecological efficiency through green technological innovation [53], while carbon-inclusion policies may reduce household emissions by strengthening awareness and green supply [54]. These studies evaluate policy outcomes at the city or household level; they do not show how users assess the rules and functions of an account-based instrument.

The closest individual-level evidence comes from personal carbon trading. Zhang and Feng use a choice experiment to study preferences over quota acquisition, trading partners, offset mechanisms, and value preservation [55]. Those attributes reflect a trading institution. The present study instead concerns voluntary accounts embedded in digital platforms, where rewards, feedback, data protection, and operating effort are more immediate features of the user experience.

Choice experiments have also been used for carbon labels, green products, personal carbon trading, and personal carbon allowances [15,17,55–60]. Collectively, this work shows that support for a low-carbon instrument is conditional on its design. It does not yet provide a clear account of how young Chinese users trade off the principal features of a voluntary personal carbon account.

Most Chinese studies of personal carbon accounts measure overall acceptance, participation intention, or policy effects. Such outcomes cannot identify whether an unfavorable response is driven by weak incentives, unconvincing feedback, privacy concerns, or the effort required to use the account. Evidence is especially limited for young adults, despite their close engagement with digital platforms and reward systems.

The analytical focus is therefore the utility attached to alternative combinations of account attributes. Benefit mechanisms, social feedback, privacy trust, and transaction costs define the main dimensions of choice, while financial literacy, environmental attitudes, and subjective knowledge are examined as possible sources of preference heterogeneity.

By locating these trade-offs within China's carbon-inclusion context, the study complements macro-level policy evaluations and personal carbon trading experiments. Its contribution is to identify which design features make a voluntary account more or less attractive to young users, while keeping the conclusions within the stated-choice setting.

3. Methods

3.1. Discrete Choice Experiment Design

The experiment follows Lancaster's characteristics approach and McFadden's random utility framework: respondents choose between schemes, and the observed choices reveal the utility associated with their attributes [61,62]. This approach is useful here because personal carbon accounts combine benefits, feedback, privacy arrangements, and operating costs that cannot be evaluated adequately through a single question about support or intention [63–66].

The account scheme was represented by five attributes drawn from the operating logic of personal carbon accounts, Chinese carbon-inclusion practice, and the literature reviewed above. Tangible welfare incentives capture directly redeemable benefits. Non-material incentives and carbon-reduction rankings represent value expression and social feedback. Privacy protection captures the account's data-protection arrangement, while overall time cost covers registration, authorization, recording, accounting, and redemption. Table 2 reports the levels and the wording used in the experiment. Two levels require a deliberately narrow interpretation. Financial credit benefits combined examples such as preferential green-loan rates and credit-score-related benefits. The coefficient therefore represents the average response to a broad financialized-benefit category as respondents understood it; it does not estimate the effect of a specific loan product or official credit record. Blockchain-based protection was presented as a technology-labeled privacy mechanism. Because the survey did not test respondents' technical understanding of blockchain, its coefficient captures the response to that label rather than the causal effect of the technology itself.

The attributes produced 108 possible profiles ($3 \times 3 \times 2 \times 2 \times 3$). Asking respondents to evaluate every combination was neither practical nor desirable. Randomized choice sets were generated through the questionnaire platform's conjoint-analysis function and then checked for level balance, attribute correlation, repetition, and anomalous tasks. The design targeted main effects and preference heterogeneity rather than higher-order interactions. Each respondent completed six randomly ordered tasks, with two alternatives in each task.

Table 2. Attributes and levels in the discrete choice experiment.

Attribute	Attribute Specification	Level	Level Description
Tangible welfare incentives	Types of tangible benefits redeemable with carbon credits	Public service benefits	Carbon credits can be redeemed for discounts on public services such as public transportation, cultural and tourism experiences, or government-provided convenience services.
		Product discount	Carbon credits can be directly deducted from cash payments when purchasing green products or engaging in daily low-carbon consumption.
		Financial credit benefits	Carbon credits can be used for preferential interest rates on green loans, additional points in credit scores, or related financial benefits.
Non-material incentives	Types of non-material incentives provided by carbon accounts	Priority access to public benefits	Users can prioritize participation in green activities, public service reservations, or low-carbon benefit exchanges
		Personal honorary title	Users can earn virtual titles on the platform, such as “Low-Carbon Leader” and “Green Youth”.
		Public welfare contribution	Users’ carbon reduction credits can be converted into tree planting, environmental donations, or support for public welfare projects.
Carbon-reduction ranking	Whether users’ carbon-reduction rankings are displayed	Yes	Show users’ carbon reduction points or ranking of carbon reduction behaviors
		No	Do not display users’ carbon reduction points or rankings of carbon reduction behaviors
Privacy protection	Data-protection approach used by the carbon account	Standard anonymization	The platform anonymizes users’ personal information and low-carbon behavior data.
		Blockchain-based protection	The platform utilizes technologies such as blockchain to document the authorization and usage processes of data, enhancing the traceability and credibility of data records.
Overall time cost	Additional daily time required to use the carbon account	0–30 min	The cumulative daily time users spend using their carbon account beyond their regular routine ranges from 0 to 30 min.
		30–60 min	The cumulative daily time users spend using their carbon account exceeds their regular daily activities by 30–60 min.
		Over 60 min	The cumulative daily time users spend using their carbon account exceeds 60 min beyond their regular daily activities.

Note: Attribute-level descriptions reproduce the wording shown to respondents. Direct cashback and coupon redemption were not included as separate tangible-welfare levels to maintain level balance and limit cognitive burden. Product discounts represent the immediate, consumption-linked benefit channel, of which cashback and coupons are operational variants.

No opt-out or status quo alternative was included. Personal carbon accounts remain unfamiliar to many potential users in China, so a status quo choice would have mixed attribute preferences with general reluctance to adopt an unfamiliar institution. The forced-choice format instead identifies relative preferences among specified schemes. The estimates should therefore be read as comparisons between account designs, not as predictions of absolute adoption. Table 3 provides an example task.

Table 3. Example of a questionnaire choice set.

Attribute	Option A	Option B
Tangible welfare incentives	Public service benefits	Financial credit benefits
Non-material incentives	Priority access to public benefits	Personal honorary title
Carbon-reduction ranking	Yes	Yes
Privacy protection	Blockchain-based protection	Blockchain-based protection
Overall time cost	0–30 min	30–60 min
Which option would you prefer to use?	☐	☐

3.2. Questionnaire, Sampling, and Data Processing

3.2.1. Questionnaire Design and Distribution

The questionnaire contained three modules. The first recorded demographic characteristics. The second measured environmental attitudes with a pre-specified ten-item shortened Chinese CNEP scale [67], subjective environmental knowledge, and financial literacy using the CHFS 2017 module. The third module contained the discrete choice experiment. Before answering the questionnaire, respondents were required to watch a short video explaining the concept, operating logic, and common applications of personal carbon accounts. Definitions of the attributes and levels were also provided before the choice tasks. Respondents then completed six tasks and selected one of two account schemes in each task.

The target population was young adults aged 18–35 years. The upper limit follows the Medium- and Long-Term Youth Development Plan (2016–2025), which defines youth in China as those aged 14–35 years [68]. The lower limit was set at 18 because the experiment involved consumption choices, financial benefits, and data authorization. The same age range is common in studies of green consumption among young Chinese adults [69,70]. Data were collected through the Credamo platform and supplementary offline surveys in major cities in Sichuan and Chongqing. Orme’s rule gives a minimum sample of 125 for this design [71]; a target above 500 was set because the planned latent class analysis required a larger sample. Students were included as digitally active potential early adopters, while the non-student sample captured young adults in early-career and other occupational settings.

3.2.2. Questionnaire Collection and Data Processing

The survey yielded 840 responses. After excluding respondents outside the target age range, incomplete questionnaires, and invalid choice-task records, 623 questionnaires remained, corresponding to a valid-response rate of 74.2%. This sample exceeded the minimum required for the choice design and provided sufficient observations for the planned heterogeneity analyses.

3.2.3. Validity Test of the Randomly Generated Choice Sets

The randomized choice design was evaluated in terms of level balance, attribute association, and task anomalies. Attribute levels were distributed close to their theoretical proportions: the largest deviation was 0.79 percentage points. All levels therefore appeared often enough to support estimation, without any level dominating the choice sets.

Pairwise associations between attributes were also small. The largest Cramer’s V was 0.034, between tangible welfare incentives and overall time cost, and the largest absolute correlation between attribute-level dummies was 0.039. The choice sets therefore contained no evident fixed pairing that would prevent the effects of individual attributes from being separated.

All 3738 tasks contained two distinct alternatives and one recorded choice. Fifty-seven tasks (1.52%) differed only in overall time cost and thus presented a particularly

clear cost comparison; their small share was unlikely to dominate estimation. Overall, the design showed adequate level coverage, limited attribute association, and no material task anomaly.

3.2.4. Data Processing

Economic resources were measured differently for students and non-students because the two groups generally rely on different income sources. Students' monthly living expenses and non-students' monthly income were converted to ordered values and standardized within each group. The resulting z-score represents a respondent's relative economic position among others with the same student status rather than an absolute comparison of income and living expenses.

Financial literacy was measured with eight objective items covering risk-return relationships, interest, inflation, financial products, market segments, bond risk, and diversification. Correct answers were coded as 1; incorrect, unknown, or non-response categories were coded as 0. The mean accuracy rate, ranging from 0 to 1, was used as the financial-literacy score.

Environmental attitudes were measured with the pre-specified ten-item shortened CNEP scale, while subjective environmental knowledge was measured with a separate multi-item scale. Items were scored in the direction of each construct before their mean values were calculated. The KMO statistics were 0.764 and 0.934, respectively, and both Bartlett tests were significant. Cronbach's alpha was 0.657 for environmental attitudes and 0.921 for subjective knowledge. Appendix A Table A1 reports corrected item-total correlations and alpha-if-item-deleted statistics. One environmental-attitude item had a corrected item-total correlation of 0.042; removing it would raise alpha to 0.711. Because item deletion was not specified before analysis, the original ten-item index was retained. Results involving environmental attitudes are therefore treated as exploratory.

3.3. Model Specification

3.3.1. Conditional Logit Model

In each task, respondent n chose between two personal carbon account schemes. Under random utility theory [62], the utility obtained from alternative j in task t is written as follows:

$$U_{ntj} = V_{ntj} + \varepsilon_{ntj} = \beta' X_{ntj} + \varepsilon_{ntj} \quad (1)$$

Here, U_{ntj} ; V_{ntj} ; X_{ntj} ; ε_{ntj} denote the notation used in the utility specification: U_{ntj} is the overall utility that respondent n obtains from alternative j in choice task t ; V_{ntj} is the observable utility component; X_{ntj} is the vector of scheme attributes, including tangible welfare incentives, non-material incentives, carbon-reduction rankings, privacy protection, and overall time cost; β is the parameter vector to be estimated; and ε_{ntj} is the random error term.

Under the conditional logit specification, if the random error terms are assumed to be independently and identically distributed Type I extreme value variables, the probability that respondent n chooses alternative j in choice task t is given by:

$$P_{ntj} = \frac{\exp(\beta' X_{ntj})}{\sum_{k=1}^J \exp(\beta' X_{ntk})} \quad (2)$$

Here, J is the number of alternatives in a choice set; $J = 2$ in this experiment. The conditional logit model identifies average utility differences associated with the attribute levels. Its main limitation is the assumption that respondents share the same preference parameters.

Nominal attributes were dummy-coded. The reference levels were public service benefits, priority access to public benefits, the presence of a ranking, and standard anonymization. Each coefficient therefore measures the utility difference between an attribute level and its stated reference category.

Each respondent made six choices, so observations from the same individual cannot be treated as independent. Conditional logit and interaction models were estimated with standard errors clustered at the respondent level.

Overall time cost was shown as 0–30 min, 30–60 min, and more than 60 min. Representative values of 15, 45, and 75 min were mean-centered for the baseline specification so that attribute utility could be converted into time-cost equivalents. The value of 75 min is only a coding of the open-ended category. Because this approach assumes a linear relationship across coarse intervals, Section 4.3 re-estimates the model with categorical time-cost indicators. The resulting time-cost equivalents are relative utility metrics, not predictions of the number of minutes users would actually spend.

$$TC_a = \frac{-\beta_a}{\beta_{time}} \quad (3)$$

Here, β_a is the estimated coefficient of attribute level a , and β_{time} is the coefficient of overall time cost. The value represents the additional time cost that would offset the utility difference between attribute level a and its baseline level. A positive value indicates that the utility gain from the attribute level can compensate for a certain amount of time cost. A negative value indicates a negative utility trade-off relative to time cost and therefore a reduction in the scheme's relative attractiveness.

3.3.2. Mixed Logit Model

The conditional logit model provides average coefficients but does not represent variation in tastes. The mixed logit model allows selected attribute coefficients to vary across respondents and relaxes both preference homogeneity and the independence-of-irrelevant-alternatives restriction [72–74].

Consistent with the attribute specification, overall time cost was treated as a fixed cost parameter, whereas the other main attribute-level parameters were treated as random parameters. The utility function for respondent n choosing alternative j in choice task t is specified as follows:

$$U_{ntj} = \beta_n' X_{ntj} + \alpha C_{ntj} + \varepsilon_{ntj}, \quad \beta_n \sim f(\beta|\theta) \quad (4)$$

Here, X_{ntj} denotes the vector of non-cost attribute-level variables; C_{ntj} denotes overall time cost; β_n is the respondent-specific random preference parameter vector; α is the fixed time-cost parameter; ε_{ntj} is the random error term; and θ denotes the parameters of the random-parameter distribution. The random parameters were assumed to follow normal distributions.

Because each respondent completed six choice tasks, the mixed logit model treats respondents as panel individuals and regards the multiple choices made by the same respondent as a complete choice sequence. Conditional on the preference parameters, the probability of respondent n 's complete choice sequence is expressed as follows:

$$L_n(\beta_n, \alpha) = \prod_{t=1}^{T_n} \left[\frac{\exp(\beta_n' X_{nt, y_{nt}} + \alpha C_{nt, y_{nt}})}{\sum_{k=1}^J \exp(\beta_n' X_{nt, k} + \alpha C_{nt, k})} \right] \quad (5)$$

Here, y_{nt} denotes the alternative actually chosen by respondent n in choice task t , and T_n denotes the total number of choice tasks completed by respondent n ; $T_n = 6$ for all

respondents. The unconditional probability of respondent n 's complete choice sequence is then given by:

$$P_n = \int L_n(\beta_n, \alpha) f(\beta_n | \theta) d\beta_n \quad (6)$$

The mixed logit model was estimated at the respondent level using the likelihood of each six-task choice sequence. Simulated maximum likelihood estimation used 1000 draws, with robust standard errors. The estimated means describe average preferences, while significant standard deviations indicate dispersion in preferences for the corresponding attributes [72].

3.3.3. Latent Class Model

A latent class model was added because continuous dispersion does not reveal whether respondents form groups with substantively different preference structures. The model assumes that respondents belong probabilistically to a finite number of classes, with relatively similar coefficients within a class and different coefficients across classes [72,75,76].

As in the mixed logit model, the latent class model accounts for the repeated-choice structure of the data. Respondents were treated as panel individuals; the six choice tasks completed by the same respondent were regarded as a choice sequence, and a sequence likelihood function was constructed at the individual level.

Assuming that the dataset contains Q latent classes, the conditional probability that respondent n chooses alternative j in choice task t , given membership in class q , is expressed as follows:

$$P_{ntj|q} = \frac{\exp(\beta_q' X_{ntj})}{\sum_{k=1}^J \exp(\beta_q' X_{ntk})} \quad (7)$$

Here, β_q denotes the attribute preference parameter vector for class q . Because each respondent made multiple choices, the conditional probability of respondent n 's complete choice sequence under class q is given by:

$$L_{n|q} = \prod_{t=1}^{T_n} P_{nt,y_{nt}|q} \quad (8)$$

Models with different numbers of classes were first estimated without membership covariates. Selection was based on log-likelihood, AIC, CAIC, BIC, parsimony, and whether the resulting classes had a coherent substantive interpretation. Individual characteristics were added to the membership equation only after the number of classes had been selected.

$$AIC = -2\ln L + 2k, \quad (9)$$

$$BIC = -2\ln L + k\ln N, \quad (10)$$

$$CAIC = -2\ln L + k[\ln N + 1] \quad (11)$$

Here, L denotes the maximum likelihood value of the model, k represents the number of parameters, and N is the respondent sample size. BIC and CAIC were prioritized, while the clarity of class interpretation was also considered when determining the final number of classes.

After membership covariates were incorporated, the probability that respondent n belonged to class q was expressed as follows:

$$\pi_{nq} = \frac{\exp(Z_n' \gamma_q)}{\sum_{l=1}^Q \exp(Z_n' \gamma_l)} \quad (12)$$

Here, Z_n denotes respondents' individual characteristics, including gender, age, relative economic status, financial literacy, environmental attitudes, and subjective environmental knowledge; γ_q denotes the parameters to be estimated in the class-membership equation. For model identification, the parameters of one class were normalized to zero. The overall probability of respondent n 's complete choice sequence is then given by:

$$P_n = \sum_{q=1}^Q \pi_{nq} L_{n|q} \quad (13)$$

The final latent class specification therefore balances statistical fit with a class structure that can be interpreted in relation to account design. Membership covariates are used to describe the characteristics associated with each class rather than to assign respondents deterministically.

4. Results

4.1. Descriptive Statistics

Tables 4 and 5 summarize the 623 respondents and the variables used in the heterogeneity analysis. All respondents were aged 18–35 and lived in the Sichuan-Chongqing region. Students accounted for 53.5% of the sample; the remaining 46.5% included professional, service, clerical, managerial, production, transport, and other occupations. Educational attainment was relatively high. Environmental attitudes were generally positive, subjective environmental knowledge was moderate to high, and financial literacy showed greater dispersion. The full distributions are reported in the tables, so the analysis below concentrates on estimated preferences.

Table 4. Distribution of demographic characteristics in the sample.

Variable	Category	Frequency	Percentage (%)
Gender	Female	411	66.0
	Male	212	34.0
Age	≤20 years	305	49.0
	21–25 years	69	11.1
	26–30 years	141	22.6
	31–35 years	108	17.3
Highest education	High school, secondary vocational school, or below	43	6.9
	Junior college	59	9.5
	Bachelor's degree	481	77.2
	Graduate degree or above	40	6.4
Occupation	Student	333	53.5
	Professional/technical personnel	98	15.7
	Commercial/service-sector personnel	67	10.8
	Clerical staff	51	8.2
	Managers in government agencies, enterprises, or public institutions	41	6.6
	Production/transportation personnel	15	2.4
	Other	18	2.9

Table 5. Descriptive statistics for the main study variables.

Variable	Mean	SD	Maximum	Minimum
Relative economic status	−0.003	1.001	3.335	−2.124
Environmental attitudes	3.823	0.445	5	2
Subjective environmental knowledge	3.458	0.749	5	1.4
Financial literacy	0.658	0.205	1	0

4.2. Average Attribute Preferences

Tables 6 and 7 report the conditional and mixed logit estimates. The two models produced similar coefficient signs and significance patterns. The conditional logit estimates are used to describe average preferences, while the mixed logit estimates are considered when the dispersion of preferences is relevant.

Table 6. Estimation results of the conditional logit baseline model.

Variable	Attribute Level	Coefficient	Standard Error
Tangible welfare incentives	Product discount	0.276 ***	0.065
	Financial credit benefits	−0.277 ***	0.065
Non-material incentives	Personal honorary title	−0.447 ***	0.064
	Public welfare contribution	−0.166 ***	0.061
Carbon-reduction ranking	No ranking	−0.180 ***	0.050
Privacy protection	Blockchain-based protection	−0.015	0.050
Overall time cost	Centered overall time cost	−0.007 ***	0.001
Observations		7476	
Log-likelihood		−2482.8144	
Prob > chi2		0.0000	

Note: *** indicate significance at the 1% levels. Standard errors are clustered at the respondent level. Overall time cost was presented as interval categories (0–30 min, 30–60 min, and >60 min) and entered into the baseline regression as a mean-centered continuous variable using representative values of 15, 45, and 75 min.

Table 7. Estimation results of the mixed logit baseline model.

Variable	Mean Coefficient	Mean Standard Error	SD Coefficient	SD Standard Error
Overall time cost	−0.009 ***	0.001	—	—
Product discount	0.360 ***	0.087	0.904 ***	0.146
Financial credit benefits	−0.404 ***	0.088	0.919 ***	0.141
Personal honorary title	−0.591 ***	0.085	0.738 ***	0.149
Public welfare contribution	−0.203 ***	0.077	0.585 ***	0.167
No carbon-reduction ranking	−0.238 ***	0.066	0.596 ***	0.135
Blockchain-based protection	−0.017	0.062	0.492 ***	0.161
Observations		7476		
Prob > chi2		0.0000		
Log-likelihood		−2449.1419		

Note: *** indicate significance at the 1% levels. Overall time cost was specified as a fixed parameter, while the other attribute levels were treated as normally distributed random parameters. Respondents were treated as panel individuals. The model used 1000 simulation draws, and robust standard errors are reported.

Relative to public service benefits, product discounts increased scheme utility, whereas financial credit benefits reduced it. The result favors a reward that is immediate and

familiar over a benefit whose eligibility and redemption may be less transparent. The latter interpretation remains tentative because respondents' understanding of financialized benefits was not measured directly. Among non-material incentives, both honorary titles and public-welfare contributions were less attractive than priority access to public benefits. On average, respondents therefore preferred an incentive with practical use over symbolic recognition or an indirect collective benefit.

The no-ranking coefficient was negative, indicating that respondents valued the presence of ranking feedback [77]. By contrast, blockchain-based protection did not differ significantly from standard anonymization in the full sample. The result concerns the blockchain label as respondents perceived it and should not be read as evidence that the two technologies provide equivalent protection.

Time cost had a negative coefficient: schemes requiring more time were less attractive. This effect is substantively important because registration, authorization, recording, and redemption are recurring parts of account use rather than one-off features.

The student and non-student subsample estimates provide a check on whether the overall pattern was driven by the large student share (Appendix A Table A2). Product discounts remained positive, time-cost effects remained negative, no-ranking coefficients remained negative, and the blockchain-labeled level remained insignificant in both subsamples. Coefficient magnitudes differed for several incentives and for high time cost, but the separate models do not formally test equality between groups. These differences are therefore descriptive rather than conclusive evidence of occupational heterogeneity.

4.3. Robustness Check: Categorical Time Cost

The time-cost attribute was re-estimated as a set of categories, with 0–30 min as the reference. The coefficients were -0.246 for 30–60 min and -0.422 for more than 60 min, and both were significant at the 1% level.

This specification removes the linearity assumption imposed by the representative values used in the baseline model. It provides a direct check of whether the negative time-cost result depends on midpoint coding.

As Table 8 shows, the penalty increased across the two higher time categories, while the remaining attribute coefficients changed little in sign or significance. The main time-cost finding is therefore robust to categorical coding. The continuous coefficient is retained only for the utility conversion reported in the next section.

Table 8. Robustness check with categorical specification of time cost.

Variable	Coefficient	Clustered Robust Standard Error	z Value	95% Confidence Interval
Product discount	0.274 ***	0.065	4.25	[0.148, 0.401]
Financial credit benefits	-0.277 ***	0.065	-4.26	$[-0.404, -0.150]$
Personal honorary title	-0.446 ***	0.064	-7.00	$[-0.570, -0.321]$
Public welfare contribution	-0.167 ***	0.061	-2.72	$[-0.286, -0.047]$
No carbon-reduction ranking	-0.180 ***	0.050	-3.60	$[-0.278, -0.082]$
Blockchain-based protection	-0.015	0.050	-0.30	$[-0.112, 0.082]$
Time cost: 30–60 min	-0.246 ***	0.062	-3.97	$[-0.367, -0.125]$
Time cost: Over 60 min	-0.422 ***	0.067	-6.30	$[-0.553, -0.291]$

Note: The 0–30 min category is the baseline. *** indicate significance at 1% levels.

4.4. Time-Cost Equivalents

Time-cost equivalents express attribute utility in relation to the estimated cost of time [78]. They are reported only after the categorical robustness check and should be read as relative model-based comparisons. In particular, the 75 min value assigned to the

open-ended category is a coding device rather than a behavioral estimate. Table 9 reports the conversions.

Table 9. Estimated time-cost conversion values (unit: min).

Attribute	Attribute Level	Time Cost Conversion WST Value	95% Confidence Interval
Tangible welfare incentives	Product discount	39.195 ***	[17.961, 60.429]
	Financial credit benefits	−39.443 ***	[−61.198, −17.688]
Non-material incentives	Personal honorary title	−63.479 ***	[−89.202, −37.755]
	Public welfare contribution	−23.597 **	[−42.052, −5.143]
Carbon-reduction ranking	No ranking	−25.526 ***	[−41.120, −9.931]
Privacy protection	Blockchain-based protection	−2.093	[−15.943, 11.758]

Note: **, and *** indicate significance at the 5%, and 1% levels, respectively.

A product discount generated utility equivalent to 39.195 min relative to public service benefits, while financial credit benefits generated an equivalent of −39.443 min. The contrast summarizes the difference between an immediate consumption benefit and the broader financialized-benefit category used in the experiment.

Honorary titles produced the largest negative equivalent (−63.479 min) relative to priority access to public benefits. Public-welfare contributions and the absence of ranking feedback also had negative equivalents. The estimate for blockchain-labeled protection was small and statistically insignificant (−2.093 min), consistent with the absence of an average preference difference from standard anonymization.

4.5. Preference Heterogeneity by Respondent Characteristics

Interaction terms were used to examine whether selected respondent characteristics were associated with different valuations of welfare and non-material incentives. Age, relative economic status, financial literacy, environmental attitudes, and subjective environmental knowledge were mean-centered before estimation. Table 10 reports the interaction coefficients.

The interaction between gender and financial credit benefits was positive but significant only at the 10% level. Age was positively associated with the valuation of public-welfare contributions, whereas relative economic status showed no stable interaction under this specification.

Financial literacy was negatively associated with the valuation of public-welfare contributions. This coefficient does not establish weaker concern for public welfare. One possible interpretation is that respondents with greater financial knowledge placed more weight on rule clarity and verifiable conversion, which are less evident for an indirect public-welfare benefit. The mechanism was not measured directly and should be treated as an interpretation rather than a separate finding.

Environmental attitudes and subjective environmental knowledge were negatively associated with product discounts and positively associated with public-welfare contributions. This pattern is compatible with a shift from personal rewards toward value-expressive benefits among respondents with stronger environmental orientations. Because the attitude scale had moderate reliability and many other interactions were insignificant, these results are exploratory.

Table 10. Results of the interaction-effect model for incentive attributes.

Variable	Coefficient	Robust Standard Error	z Value	95% Confidence Interval
Product discounts × Financial literacy	0.363	0.321	1.13	[−0.267, 0.993]
Financial credit benefits × Financial literacy	−0.399	0.322	−1.24	[−1.030, 0.233]
Personal honorary title × Financial literacy	−0.451	0.330	−1.37	[−1.098, 0.196]
Public welfare contribution × Financial literacy	−0.876 ***	0.310	−2.83	[−1.484, −0.269]
Product discounts × Environmental attitudes	−0.444 ***	0.136	−3.26	[−0.710, −0.177]
Financial credit benefits × Environmental attitudes	−0.185	0.151	−1.22	[−0.481, 0.112]
Personal honorary title × Environmental attitudes	−0.029	0.149	−0.20	[−0.322, 0.263]
Public welfare contribution × Environmental attitudes	0.264 **	0.127	2.09	[0.016, 0.512]
Product discounts × Subjective environmental knowledge	−0.159 *	0.082	−1.93	[−0.320, 0.003]
Financial credit benefits × Subjective environmental knowledge	0.052	0.087	0.60	[−0.119, 0.224]
Personal honorary title × Subjective environmental knowledge	−0.087	0.089	−0.98	[−0.260, 0.087]
Public welfare contribution × Subjective environmental knowledge	0.171 **	0.086	1.98	[0.001, 0.340]
Product discounts × Gender	0.015	0.134	0.11	[−0.248, 0.277]
Financial credit benefits × Gender	0.242 *	0.140	1.73	[−0.032, 0.516]
Personal honorary title × Gender	−0.009	0.129	−0.07	[−0.262, 0.244]
Public welfare contribution × Gender	0.118	0.131	0.90	[−0.139, 0.374]
Product discounts × Age	0.006	0.012	0.47	[−0.018, 0.029]
Financial credit benefits × Age	0.020	0.012	1.62	[−0.004, 0.043]
Personal honorary title × Age	0.005	0.011	0.47	[−0.017, 0.028]
Public welfare contribution × Age	0.037 ***	0.011	3.30	[0.015, 0.060]
Product discounts × Relative economic status	−0.060	0.060	−1.01	[−0.178, 0.057]
Financial credit benefits × Relative economic status	0.031	0.067	0.46	[−0.101, 0.162]
Personal honorary title × Relative economic status	0.011	0.064	0.17	[−0.115, 0.137]
Public welfare contribution × Relative economic status	0.040	0.062	0.65	[−0.081, 0.162]

Note: The model controls for the main effects of all account attributes; only the core interaction terms are reported. Standard errors are clustered at the respondent level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.6. Latent Class Model Results

4.6.1. Determining the Number of Classes

Adding classes improved log-likelihood and reduced AIC, but BIC and CAIC reached their lowest values for the two-class model. Models with more classes offered less distinct interpretations, and specifications with four or more classes were unstable once membership covariates were added. The two-class solution was therefore retained as the best balance between fit, parsimony, and substantive clarity (Table 11 and Appendix A Table A3).

Table 11. Comparison of latent class models without membership covariates.

Number of Classes	Log-Likelihood	Number of Parameters	AIC	CAIC	BIC
2 classes	−2456.843	15	4943.687	5025.205	5010.205
3 classes	−2434.940	23	4915.881	5040.875	5017.875
4 classes	−2419.537	31	4901.074	5069.544	5038.544
5 classes	−2410.978	39	4899.956	5111.904	5072.904
6 classes	−2406.000	47	4906.000	5161.424	5114.424
7 classes	−2390.498	55	4890.996	5189.896	5134.896
8 classes	−2388.736	63	4903.472	5245.848	5182.848

Note: Table 11 compares models without class-membership covariates. After the two-class solution was selected, individual characteristics were incorporated into the membership equation.

4.6.2. Preference Parameters by Class

The two-class solution separates a smaller group that valued product discounts and the blockchain label from a larger group whose preferences centered on low burden and simple feedback (Table 12). The class names are descriptive labels based on these coefficient patterns, not direct measures of respondents' motivations.

Table 12. Estimation results of the two-class latent class model.

Variable	Class 1		Class 2	
	Coefficient	Standard Error	Coefficient	Standard Error
Product discount	2.822 ***	1.071	0.019	0.091
Financial credit benefits	−0.547	0.460	−0.264 ***	0.079
Personal honorary title	−1.818 ***	0.644	−0.331 ***	0.078
Public welfare contribution	−1.372 **	0.588	−0.054	0.074
No carbon-reduction ranking	−0.981 **	0.423	−0.109 *	0.059
Blockchain-based protection	0.652 *	0.345	−0.091	0.061
Overall time cost	−0.030 ***	0.009	−0.005 ***	0.001
Gender	−0.248	0.434	—	—
Age	0.045	0.037	—	—
Relative economic status	−0.343 *	0.194	—	—
Financial literacy	4.364 ***	1.24	—	—
Environmental attitudes	−0.354	0.441	—	—
Subjective environmental knowledge	−0.301	0.262	—	—
Proportion	18.3%		81.7%	

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Following Hanemann's framework, time-cost equivalents were calculated as the ratio of each attribute-level coefficient to the time-cost coefficient. These values represent model-based utility trade-offs rather than actual minutes respondents would spend.

The pragmatic trust-oriented class represented 18.3% of respondents. It showed positive coefficients for product discounts and blockchain-labeled protection and negative coefficients for honorary titles, public-welfare contributions, and ranking. Time cost was also negative. The pattern suggests a preference for immediate benefits and explicit protection cues, provided that the account remains convenient to use.

The minimal feedback-oriented class represented 81.7% of respondents. Financial credit benefits and honorary titles were unattractive, while product discounts and blockchain-labeled protection were not statistically significant. The negative no-ranking coefficient indicates that this class still valued a basic form of comparative feedback, and the negative time-cost coefficient shows a strong preference for low-burden participation.

Financial literacy was positively associated with membership in the pragmatic trust-oriented class. Relative economic status had a negative association at the 10% level and should be interpreted cautiously. Gender, age, environmental attitudes, and subjective environmental knowledge did not significantly predict class membership. These covariates describe probabilistic associations with class membership rather than fixed user types.

5. Discussion

5.1. Theoretical Implications: From Attitudes to Design Trade-Offs

The results qualify a common assumption in low-carbon behavior research: favorable environmental attitudes do not determine which account scheme a user will choose. In the experiment, respondents compared concrete benefits, feedback, privacy cues, and operating effort. Account design therefore enters the attitude-behavior relationship as part of the decision environment rather than as a neutral delivery mechanism.

The incentive results are consistent with the importance of reward immediacy and accessibility [40,41]. The ranking result supports the role of visible social comparison [43–45], but the weak performance of honorary titles shows that not every symbolic signal carries the same value. Privacy calculus is reflected less in the average blockchain coefficient than in its dispersion: a technical label generated different responses across users and classes, without producing a uniform advantage [47–50]. The negative time-cost coefficient, in turn, shows how participation friction can limit perceived behavioral control [26]. The exploratory interaction results add a further qualification: environmental attitudes may alter the type of benefit valued, but they do not remove the trade-offs created by account design [69,79].

5.2. Incentive and Feedback Design for Young Users

The incentive results favor benefits that are immediate, familiar, and easy to redeem. This is not simply a preference for monetary rewards. Product discounts performed better than public service benefits, but the broader financialized-benefit category performed worse, indicating that the form and accessibility of the benefit matter.

Financial benefits linked to loans or credit may carry eligibility conditions, delayed value, or uncertainty about redemption. These features are plausible reasons for their lower average coefficient, particularly among students and early-career respondents, but the survey did not test those explanations directly. For design purposes, the safer inference is that complex financial benefits should not be used as the sole or primary entry incentive. The result is consistent with research on the adoption and continued use of Ant Forest and other personal carbon account platforms [80–82].

Feedback should also be concrete. Respondents valued ranking, yet they did not favor honorary titles over priority access to public benefits. A ranking gives users an immediate reference point; an honorary title has little informational value unless it is tied to a visible achievement. Platforms could therefore link recognition and public-welfare contributions to recorded emission reductions, staged goals, and verifiable outcomes rather than relying on generic labels.

The experiment did not distinguish product discounts from coupons or direct cashback. The product-discount coefficient therefore represents one immediate consumption-linked channel, not all monetary incentives. Future experiments should separate these forms. The student and non-student estimates also suggest that campus and early-career settings may not respond identically, although formal interaction tests are needed before treating the differences as established segmentation effects.

5.3. Privacy Trust and Technology Labels

The privacy result is best understood as a difference between an average and a distribution. Blockchain-labeled protection did not outperform standard anonymization in the full sample, but its random-parameter standard deviation was significant (0.492, $p < 0.01$), and the positive coefficient was concentrated in the smaller latent class. The average therefore conceals disagreement about the label. Because the questionnaire did not measure tech-

nical understanding, the source of that disagreement cannot be separated into familiarity, perceived security, or trust in the institution using the technology.

This distinction matters for privacy calculus. Users do not encounter data protection as a technical architecture alone; they encounter explanations of what data are collected, who can use them, how long they are retained, and whether consent can be withdrawn. A platform should therefore explain these rights and procedures in ordinary language rather than use blockchain as a proxy for trust. Future studies should measure technical familiarity, perceived control over data, and institutional trust separately.

5.4. Design and Policy Implications

Public agencies have a coordinating role that individual platforms cannot perform. Common accounting standards, clear authorization rules, and cross-platform recognition would make account benefits more predictable. Public-service rewards are likely to be more useful when they are embedded in familiar settings such as public transport, cultural services, and local green consumption.

Platform design should minimize recurring effort. Registration and authorization should be short, point rules should be visible, and redemption should occur without unnecessary thresholds or delays. Progress feedback can remain simple, while honorary recognition should be tied to a verifiable reduction outcome rather than assigned as a generic title.

Financial institutions should distinguish platform green points, commercial credit assessment, and official personal credit records. Presenting these mechanisms as a single benefit risks creating expectations that the account cannot meet. Financialized rewards may be useful for selected users, but the results do not support treating them as a universal incentive.

The latent classes suggest two broad design emphases rather than two fixed products. Users resembling the pragmatic trust-oriented class may respond to direct discounts and clearly explained protection options. The larger minimal feedback-oriented class calls for a simpler default: low time cost, transparent rules, and basic ranking feedback. Segmentation should remain optional and evidence-based because class membership is probabilistic.

5.5. Scope Conditions and Research Priorities

The study was designed to identify account preferences among young adults in the Sichuan-Chongqing region. This focus is appropriate for a group with extensive exposure to digital platforms and carbon-inclusion campaigns, but it does not support generalization to other ages, regions, or occupational structures. The student and non-student analysis addresses one aspect of this boundary without making the sample nationally representative.

The forced-choice format identifies trade-offs among account schemes, not the probability that a person would adopt an account. An opt-out alternative was omitted because many respondents lacked an established personal carbon account that could serve as a meaningful status quo. As real-world experience accumulates, opt-out designs will be better able to separate scheme preference from non-participation.

The attribute levels were kept broad so that six choice tasks remained manageable and the design retained adequate balance. This choice supports estimation of the main design channels but prevents finer distinctions among cashback, coupons, green-loan discounts, platform credit points, and official credit-related benefits. More focused experiments or adaptive designs could examine these subtypes.

Respondents watched an introductory video and received definitions of personal carbon accounts, attributes, and levels before making their choices. These procedures

standardized the general decision context, but they were not substitutes for attribute-specific cognitive interviews or manipulation checks. The study therefore cannot establish that respondents interpreted financialized benefits or blockchain-labeled protection in the same way. Follow-up work should test these interpretations directly and distinguish technical familiarity, perceived data control, and institutional trust.

The environmental-attitude scale had moderate internal consistency (Cronbach's $\alpha = 0.657$), so the related interaction results remain exploratory. Future research should combine more reliable short-form scales with broader occupational samples and observed platform behavior. Linking stated choices to registration, redemption, and continued use would show whether the preferences identified here persist outside the experiment.

6. Conclusions

This study used a discrete choice experiment with 623 young adults in the Sichuan-Chongqing region to examine how personal carbon account design affects stated preferences. Conditional logit, mixed logit, and latent class models were used to estimate average effects and preference heterogeneity.

Three results are central. Product discounts and ranking feedback made account schemes more attractive, whereas higher time costs reduced their appeal; financial credit benefits, honorary titles, and public-welfare contributions were less attractive than their reference levels. Blockchain-labeled protection had no average advantage over standard anonymization, but responses to the label varied across individuals and classes. The two latent classes further show that immediate benefits and protection cues mattered to a minority, while the larger group placed greater weight on low operating burden and simple feedback.

The evidence shifts the design question from whether young adults support personal carbon accounts to which combinations of features they prefer. Within the stated-choice setting, attractive schemes paired understandable and accessible benefits with visible feedback, limited participation effort, and concrete explanations of data protection.

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Institutional Review Board Statement: This study was waived for ethical review as the study used an anonymous questionnaire survey and a discrete choice experiment to examine young adults' preferences for personal carbon account designs in the Sichuan-Chongqing region of China. The research did not involve medical intervention, clinical trials, biological sample collection, or any procedure that could affect participants' physical or psychological health. All data were used only for academic research and reported in aggregate form. Because the study is a low-risk social science survey and meets the conditions for exemption from full ethical review by Institution Committee.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Reliability diagnostics for the environmental-attitude scale.

Item	Corrected Item-Total Correlation	Cronbach's Alpha If Item Deleted
Approaching the limit of Earth's carrying capacity	0.303	0.636
Human interference with nature often produces disastrous consequences	0.339	0.629
Humans are seriously abusing the environment	0.483	0.601
Plants and animals have the same right to exist as humans	0.393	0.627
Humans are subject to the laws of nature	0.377	0.626
Earth is like a spaceship with limited space and resources	0.342	0.628
The balance of nature is delicate and easily upset	0.419	0.612
If things continue, we will experience a major ecological catastrophe	0.452	0.607
The balance of nature is strong enough to cope with industrial impacts	0.042	0.711
The ecological crisis has been exaggerated	0.287	0.643

Note: The environmental-attitude items were adapted from the Chinese-context CNEP scale reported in [67].

Table A2. Robustness check by student and non-student subsamples.

Variable	Full Sample	Students	Non-Students
Product discounts	0.274 *** (0.065)	0.264 *** (0.086)	0.273 *** (0.098)
Financial credit benefits	−0.277 *** (0.065)	−0.408 *** (0.093)	−0.132 (0.092)
Personal honorary titles	−0.446 *** (0.064)	−0.463 *** (0.090)	−0.434 *** (0.090)
Public welfare contributions	−0.167 *** (0.061)	−0.340 *** (0.083)	0.038 (0.091)
No carbon-reduction ranking	−0.180 *** (0.050)	−0.168 ** (0.069)	−0.208 *** (0.073)
Blockchain-based protection	−0.015 (0.050)	−0.082 (0.067)	0.074 (0.074)
Time cost: 30–60 min	−0.246 *** (0.062)	−0.169 * (0.090)	−0.334 *** (0.086)
Time cost: Over 60 min	−0.422 *** (0.067)	−0.297 *** (0.087)	−0.572 *** (0.104)
Observations	7476	3996	3480
Respondents	623	333	290
Pseudo R ²	0.0418	0.0467	0.0486

Note: Robust standard errors clustered at the respondent level are reported in parentheses. The conditional logit models were estimated separately for the full sample and the student and non-student subsamples. Baseline levels are public service benefits, priority access to public benefits, ranking display, standard anonymization, and low time cost. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A3. Comparison of information criteria for latent class models with membership covariates.

Number of Classes	Log-Likelihood	Number of Parameters	AIC	CAIC	BIC
2 classes	−2446.175	21	4934.351	5048.476	5027.476
3 classes	−2411.886	35	4893.772	5083.981	5048.981

Note: Table A3 presents information criteria after membership covariates were incorporated. These covariates include gender, age, relative economic status, financial literacy, environmental attitudes, and subjective environmental knowledge.

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