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Trust Evaluation System Construction and Empirical Research of BNPL Platform Based on Reconstructed 5C Model

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Abstract: *Building upon the traditional 5C credit evaluation framework, this study develops a user-centric trust assessment system for BNPL platforms targeting college students. The framework integrates key factors including accounting transparency and e-commerce service quality, establishing a multi-tiered indicator structure comprising five dimensions: character, capability, capital, collateral, and condition. Quantitative analysis of survey data through the Analytic Hierarchy Process (AHP) reveals distinct decision-making priorities among students: the "character" dimension (particularly platform compliance and brand credibility) ranks highest, followed by "capability" (with technical reliability as the core focus), and then "capital" (cost transparency). In contrast, "safeguards" related to data security and "condition" concerning macro-environmental factors receive comparatively lower attention. The findings demonstrate that young consumers prioritize mitigating short-term transaction risks over long-term structural risks. These insights provide critical guidance for enhancing personal finance education, improving fintech corporate governance, and optimizing relevant policy frameworks.*

Key Words: *buy now pay later, college students, 5C model reconstruction, analytic hierarchy process, trust evaluation system.*

1. INTRODUCTION:

The digital consumption wave has swept across the globe, profoundly reshaping consumer behavior. In this context, Buy Now, Pay Later (BNPL) has emerged as a significant force, rapidly permeating various aspects of daily economic life. Among these, college students, with their unique consumption patterns, have become the primary user group for BNPL, the mainstream credit consumption model. E-commerce platforms seamlessly integrate BNPL services featuring instant approval and interest-free installment plans into their consumption processes, precisely catering to the younger generation's demand for advanced consumption and convenience. This significantly lowers the consumption threshold, leading to rapid adoption among this demographic. However, the surge in BNPL demand also brings potential risks, such as excessive debt and data privacy breaches, which are becoming increasingly prominent. Therefore, how college students can rationally evaluate and select online platforms has become a topic of both theoretical and practical significance.

Current academic research on credit risk primarily remains confined to the traditional 5C model, focusing mainly on how platforms assess user creditworthiness while rarely examining the behavioral characteristics of users as key participants and the underlying reasons. This single-perspective approach makes research outcomes difficult to meet practical application standards. To address these limitations, this study proposes an innovative research framework: shifting from the conventional "top-down" evaluation to a user-centered "reverse evaluation" approach. Building upon this, we reconstruct a new 5C theoretical system and develop a comprehensive credit assessment tool specifically designed for college students in BNPL scenarios. By integrating accounting transparency metrics with e-commerce service quality factors, this tool not only assists students in making rational decisions but also provides empirical evidence for advancing personal financial management education, optimizing corporate strategies, and improving industry regulation.

2. LITERATURE REVIEW:

2.1 BNPL Model for College Students

Amid the digital consumption wave, BNPL has emerged as the world's most popular credit consumption model, particularly favored by young demographics (Tang et al., 2025). With its instant approval and interest-free installment features, this model perfectly caters to the needs of emerging consumer groups like college students for advanced consumption and convenience.

College students are digital natives and the primary users of BNPL services. Their acceptance and adoption of BNPL are influenced by various factors. Van Tuan et al. (2024) conducted an empirical study on Vietnam's Gen Z, and the results showed that social influence had the best predictive effect on attitudes and willingness to use BNPL, far surpassing other variables such as perceived benefits and ease of use. This indicates that peer behavior and social environment play a significant role in students' consumption decisions. Similar findings exist in the context of China: Zhu et al. (2021) studied Chinese college students and found that frequent internet use leads to increased credit consumption. The underlying mechanism is that online shopping activities intensify social comparison, thereby reinforcing students' materialistic values and ultimately resulting in more online consumption. This study reveals the psychological motivations behind competitive and advanced consumption among student groups, highlighting that their credit decisions are a combination of economic rationality and deep psychosocial attributes.

The BNPL model, with its instant approval and zero-interest installment features, has precisely met the consumption needs of college students, leading to rapid adoption among this demographic. However, this convenient financing model conceals numerous risks, with excessive debt among young people becoming increasingly prominent. These negative impacts extend beyond economic dimensions, eroding individuals 'subjective well-being through complex pathways. Fan and Ryu's (2023) empirical study based on the stress process theory reveals that debt, as a significant psychological stressor, significantly reduces life satisfaction in the younger generation through the mediating effects of social and personal resources. More notably, traditional family financial assistance, which is generally perceived as supportive, may paradoxically produce unintended negative effects in this context. This demonstrates how the digital financial environment is challenging conventional support systems, gradually diminishing their applicability. To address this, it is essential to strengthen personal financial management education for young people, helping them establish rational consumption attitudes and risk identification capabilities. Simultaneously, developing scientific evaluation tools tailored for BNPL scenarios is crucial to provide systematic decision-making references, guiding young people to enjoy financial convenience while avoiding potential risks and achieving reasonable consumption.

2.2 Evolution of Credit Evaluation Models

In the field of credit risk identification and management, traditional evaluation paradigms are being profoundly transformed by fintech-driven innovations. The 5C model, long regarded as the quintessential framework for financial institutions to assess borrower creditworthiness, operates on the core assumption that institutions conduct one-way evaluations of borrowers (Muhammad & Melemi, 2021). The evolution of fintech has fundamentally disrupted this unidirectional logic, shifting risk assessment data from traditional financial metrics to extensive use of alternative and behavioral data. In this process, the value of digital footprints—behavioral data left by users online—has become increasingly prominent. Berg et al. (2020) conducted groundbreaking research demonstrating that easily accessible variables in digital footprints can provide predictive information about consumer defaults comparable to traditional credit scores. This indicates that user behavior itself has emerged as a new credit benchmark, representing a revolutionary shift in the data foundation of risk assessment.

Methodologically, as data evolves toward higher dimensions and diversity in the Industry 4.0 era, credit assessment technologies powered by artificial intelligence are undergoing continuous refinement. Lu et al. (2025) addressed the challenges of big data analysis in SME credit by developing an AI classification framework with an innovative feature screening mechanism. Their research demonstrates that traditional credit evaluation systems relying on static financial indicators are being progressively replaced by dynamic, scenario-adaptive intelligent assessment methods.

The aforementioned transformation has profoundly impacted the financial sector. As Liu et al. (2025) noted, financial technology (fintech) has significantly reshaped commercial banks'risk management frameworks through multiple approaches, including enhanced operational efficiency and refined risk control models. This study not only elucidates fintech's crucial role in risk management but also provides substantial theoretical support for its strategic position within the global financial system.

2.3 Digital Credit Ecosystem

In the platform-driven digital credit ecosystem, the formation of user trust is intertwined with service convenience while being shaped by platform governance efficacy, information transparency, and data ethics standards. Aldboush and

Ferdous (2023) addressed ethical dilemmas in fintech's big data and AI applications by proposing three key strategies: strengthening data ownership safeguards, enhancing privacy protection mechanisms, and improving algorithmic fairness. Transparency serves as the cornerstone of trust-building. As highlighted in Berg et al.' s (2022) authoritative review on fintech lending, data privacy and regulatory challenges remain central issues, underscoring the critical importance of platforms' disclosure practices and regulatory compliance. Any algorithmic bias or implicit discrimination risks creating structural vulnerabilities in platform trust.

In terms of data privacy protection, the preferences and practices of users and platforms are crucial. Koul et al. (2024) conducted a study on India's digital lending system, and the results showed that both users and providers prioritize personal information concerns as a highly prioritized criterion. This conclusion directly supports the creation of collateral-related dimensions in the BNPL platform evaluation system, highlighting the core role of specific measures such as data protection and third-party constraints in building user trust. While enjoying the convenience brought by fintech, we should be cautious about the new risk characteristics hidden within it. Li (2022) found a significant risk contagion phenomenon in the China P2P online lending industry during his empirical research. This research provides important insights for the BNPL model. In the process of promoting financial innovation, it is essential to establish detailed risk management mechanisms and optimize transparent regulatory frameworks to prevent risks emerging from individual platforms from escalating into systemic crises.

While some scholars have developed relatively systematic theoretical frameworks for credit evaluation and trust mechanisms, empirical studies on college students 'cognitive preferences toward BNPL platforms remain scarce. The traditional 5C model demonstrates notable limitations in digital finance applications, as its constituent factors and corresponding scopes have undergone significant transformations. Directly applying this model to user scenarios often fails to meet practical demands. This research aims to facilitate a paradigm shift from "platform-centric" to "user-focused" approaches, reinterpreting the classic 5C framework while incorporating accounting transparency, e-commerce platform service quality, and performance metrics. The ultimate goal is to establish a comprehensive evaluation system tailored to contemporary college students' characteristics and applicable to BNPL platforms as a whole.

3. RESEARCH METHOD:

3.1 Research Design

3.1.1 Analytic Hierarchy Process

To scientifically quantify college students' evaluation preferences for BNPL platforms, this study adopts the Analytic Hierarchy Process (AHP) as the primary assessment tool. As a theoretical framework within the Multi-Criteria Decision-Making (MCDM) domain, AHP decomposes complex unstructured problems into multi-level factor systems. It converts expert subjective judgments into objective quantitative weights through sequential comparison of relative importance among indicators at each level (Saaty, 1990; Zavadskas et al., 2014). Particularly when dealing with multiple interrelated and potentially conflicting objectives, this method demonstrates exceptional adaptability and flexibility.

The effective implementation of AHP relies on a rigorous process: first, constructing a multi-level structural model that accurately captures the essence of the problem. Next, the 1-9 scale is used to quantify decision-makers' subjective perceptions of relative importance among factors, forming a corresponding judgment matrix. Through solving the eigenvectors, both local and global weight values are derived, followed by a strict consistency check (typically with a consistency ratio C.R. <0.1) to ensure logical coherence within the evaluation process (Mursalim & Mardainis, 2016). This rigorous methodology ensures the scientific validity and credibility of the final weight results.

3.1.2 Construction of AHP Evaluation Index System

Based on the theory of AHP, this paper constructs a three-level hierarchical structure model to analyze and explore the main problem of "the BNPL platform for college students' evaluation".

The top layer (highest level) defines the ultimate research objective: to complete a comprehensive evaluation of the BNPL platform by university students.

Guideline Level (Core Architecture): As a pivotal component of the evaluation framework, this study innovatively restructures the traditional 5C model's core dimensions for BNPL scenarios and user-centric perspectives. The theoretical foundation derives from two key studies: Muhammad and Melemi (2021) demonstrated the foundational role of 5Cs (Character, Capability, Capital, Collateral, Condition) in credit risk management, establishing a classical theoretical framework; while Berg et al. (2022) highlighted how technology-enabled lending exhibits new characteristics in customer interaction, data utilization, and risk patterns, emphasizing transparency, data privacy, and algorithmic governance as critical factors influencing user trust and platform evaluation. These insights guide our expansion of dimensions in digital finance contexts—redefining "capital" as "fee transparency" and "collateral" as "data protection." Building on these references, we establish five core dimensions (Table 1) with their specific implications for BNPL platform assessments. The 5C model serves as the theoretical basis due to its universal applicability and logical coherence, enabling systematic transition from traditional credit evaluation to trust assessment in digital platforms. This study reconstructs the core concepts through a user-oriented contextual approach, not only maintaining the analytical framework of classical theories but also providing a practical analytical tool for investigating trust formation mechanisms in digital credit ecosystems. Building upon this foundation, future research could further refine indicator specifications and deepen hierarchical analysis.

Indicator Level (Bottom Layer): To ensure the scientific validity and reliability of the evaluation results, this study refined the primary indicators in the criterion layer into quantifiable secondary indicators. The following principles were strictly adhered to during construction: Theoretical Support—Each secondary indicator was designed based on mature theoretical foundations (such as Signal Transmission Theory, Social Cognitive Theory, and Technology Acceptance Model), ensuring its measurement effectiveness; Empirical Basis—Extensive review and synthesis of nearly 40 related literature documents provided sufficient academic validation for each indicator, accurately reflecting the key factors currently recognized by the academic community in forming user trust and influencing decision-making; Contextual Fit—All descriptions were tailored to the actual operational status of the China BNPL platform and the consumption behavior characteristics of Chinese college students.

After the above construction, we finally get 5 first-level indicators and 25 second-level indicators, forming a complete and detailed evaluation index system. The index explanation, theoretical support and literature support are shown in Table 1-6.

Table 1 Overview of 5C Dimensions for BNPL Platform Evaluation

Dimension Code	Dimension Name	Core Connotation
C1	Character	Refers to whether the platform is legal, ethical, and trustworthy
C2	Capacity	Refers to whether the platform's application is smooth, customer service is efficient, and services are stable and reliable
C3	Capital	Refers to whether the platform's terms such as contracts and fees are clear and transparent, with no hidden charges
C4	Collateral	Refers to the platform's ability to protect users' personal information and data security
C5	Condition	Refers to whether the platform is highly compatible with your consumption scenarios (e.g., e-commerce platforms) and whether its policies are favorable

Table 2 Detailed Indicators of C1 Character Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C1-1	Compliance Certification	Whether the platform holds a formal financial license issued by the state for legal operation	Signaling Theory	Threadgold et al. (2025); Shehadeh et al. (2025); Amalia et al. (2025)
C1-2	Reputation Trust	Whether the platform has a good reputation and brand image among users and is trustworthy	Social Trust Theory	Martínez-López et al. (2021); Chen & Huang (2025); Aldboush & Ferdous (2023); Desai & Jindal (2024)
C1-3	Complaint Response	Whether the platform handles user complaints quickly, effectively, and fairly when users encounter problems	SERVQUAL Service Quality Theory	Кутбі et al. (2024); Bourne (2020); Budiarti et al. (2023); Relja et al. (2024)
C1-4	Social Responsibility	Whether the platform focuses on promoting rational borrowing and actively assumes responsibilities to users and society	Corporate Social Responsibility Theory	Threadgold et al. (2025); Кутбі et al. (2024); Fitrisam et al. (2025); Fan & Ryu (2023)

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Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C1-5	Ethical Constraints	Whether the platform's advertisements and marketing are authentic and honest, without exaggeration or misleading content	Moral Norms Theory	Threadgold et al. (2025); Bourne (2020); Amir et al. (2025); Amalia et al. (2025)

Table 3 Detailed Indicators of C2 Capacity Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C2-1	System Stability	Whether the platform's App or website operates smoothly, and core functions (e.g., payment, repayment) remain stable and reliable	Information Systems Success Model	Berg et al. (2020); Mahmud et al. (2024); Chen & Huang (2025)
C2-2	Service Responsiveness	Whether customer service (including human and intelligent customer service) can respond promptly and resolve users' problems effectively	SERVQUAL Service Quality Theory	Budiarti et al. (2023); Chen & Huang (2025); Relja et al. (2024); Bourne (2020)
C2-3	Functional Ease of Use	Whether the platform's core functions (e.g., bill checking, repayment, installment payment) are designed simply and easy to operate	Technology Acceptance Model	Berg et al. (2020); Mahmud et al. (2024); Amalia et al. (2025); Tang et al. (2025)
C2-4	Trust Cultivation	Whether the platform enables users to develop long-term trust through high-quality services and transparent communication	Trust Formation Theory	Aldboush & Ferdous (2023); Chen & Huang (2025); Shehadeh et al. (2025); Desai & Jindal (2024)
C2-5	Technical Safeguards	Whether the platform adopts effective measures to protect users' account security and payment security	Information Security Management Theory	Aldboush & Ferdous (2023); Koul et al. (2024); Li (2022); Amalia et al. (2025)

Table 4 Detailed Indicators of C3 Capital Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C3-1	Fee Transparency	Whether the platform clearly and prominently displays the real Annual Percentage Rate (APR) of loans and all types of fees	Information Asymmetry Theory	Rerung et al. (2024); Bourne (2020); Amir et al. (2025)
C3-2	Contract Clarity	Whether the platform's user agreements and loan contracts are written in simple and understandable language, without incomprehensible complex clauses	Contract Theory	Bourne (2020); Amir et al. (2025); Rerung et al. (2024)
C3-3	Cost Fairness	Whether the platform has no hidden additional charges (e.g., service fees, management fees) beyond the clearly stated interest	Fair Transaction Theory	Rerung et al. (2024); Bourne (2020); Amir et al. (2025)

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C3-4	Marketing Authenticity	Whether the rules of the platform's promotional activities (e.g., "interest-free installments") are authentic and simple, without misleading or exaggerated publicity	Signaling Theory	Amalia et al. (2025); Bourne (2020); Amir et al. (2025); Threadgold et al. (2025)
C3-5	Information Disclosure	Whether the platform proactively and completely informs users of key information such as all fee standards, repayment rules, and consequences of overdue payments	Transparency Theory	Rerung et al. (2024); Bourne (2020); Amir et al. (2025); Relja et al. (2024)

Table 5 Detailed Indicators of C4 Collateral Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C4-1	Data Protection	Whether the platform adopts effective technical measures (e.g., data encryption) to prevent users' personal information from being leaked or stolen	Privacy Protection Theory	Aldboush & Ferdous (2023); Koul et al. (2024); Li (2022); Amalia et al. (2025)
C4-2	Clear Authorization	Whether the platform's privacy policy clearly specifies which information will be collected and for what purposes, enabling users to understand the authorization scope	Legal Contract Theory	Aldboush & Ferdous (2023); Koul et al. (2024); Amir et al. (2025); Relja et al. (2024)
C4-3	Third-party Restrictions	Whether the platform strictly restricts the provision of users' data to other companies and does not share it arbitrarily without users' consent	Risk Mitigation Theory	Aldboush & Ferdous (2023); Koul et al. (2024); Li (2022); Rerung et al. (2024)
C4-4	Certification Assurance	Whether the platform has obtained national or internationally recognized security certifications, proving that its data protection capabilities meet standards	Signaling Theory	Amalia et al. (2025); Aldboush & Ferdous (2023); Rerung et al. (2024); Shehadeh et al. (2025)
C4-5	Privacy Self-control	Whether users can conveniently check, manage, or delete their personal information and have control over their own privacy data	Information Privacy Management Theory	Aldboush & Ferdous (2023); Koul et al. (2024); Relja et al. (2024); Amir et al. (2025)

Table 6 Detailed Indicators of C5 Condition Dimension

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
C5-1	Policy Adaptation	Whether the platform strictly complies with national regulatory policies on college students' credit (e.g., credit limit restrictions, interest rate caps)	Institutional Theory	Shehadeh et al. (2025); Li (2022); Liu et al. (2025)
C5-2	Market Integration	Whether the platform is deeply integrated with mainstream e-commerce platforms (e.g., Taobao,	Network Effect Theory	Chen & Huang (2025); Tang et al. (2025);

Indicator Code	Indicator Name	Indicator Description	Theoretical Support	Literature Support
		JD.com) to provide a smooth and convenient payment experience		Desai & Jindal (2024)
C5-3	Scenario Expansion	Whether the platform supports usage in various life scenarios (e.g., offline shopping, education payment, travel consumption)	Ecosystem Theory	Tang, J. A. (2019); Fitrisam et al. (2025); Relja et al. (2024)
C5-4	Credit Matching	Whether the credit limit provided by the platform matches users' actual consumption needs and repayment capabilities	Credit Matching Theory	Fitrisam et al. (2025); Relja et al. (2024); Amir et al. (2025)
C5-5	Environmental Sensitivity	Whether the platform can flexibly adjust its service strategies according to changes in economic conditions and user needs	Context-Aware Decision Theory	Liu et al. (2025); Li (2022); Rerung et al. (2024)

The establishment of this hierarchical model provides a foundation for subsequent data collection through pairwise comparison questionnaires and relative weight calculation of hierarchical elements, enabling the capture of complex and implicit decision-making preferences among college students. The BNPL platform evaluation index system for college students, constructed based on the 5C theory, is illustrated in Figure 1: College Students' BNPL Platform Evaluation Index System.

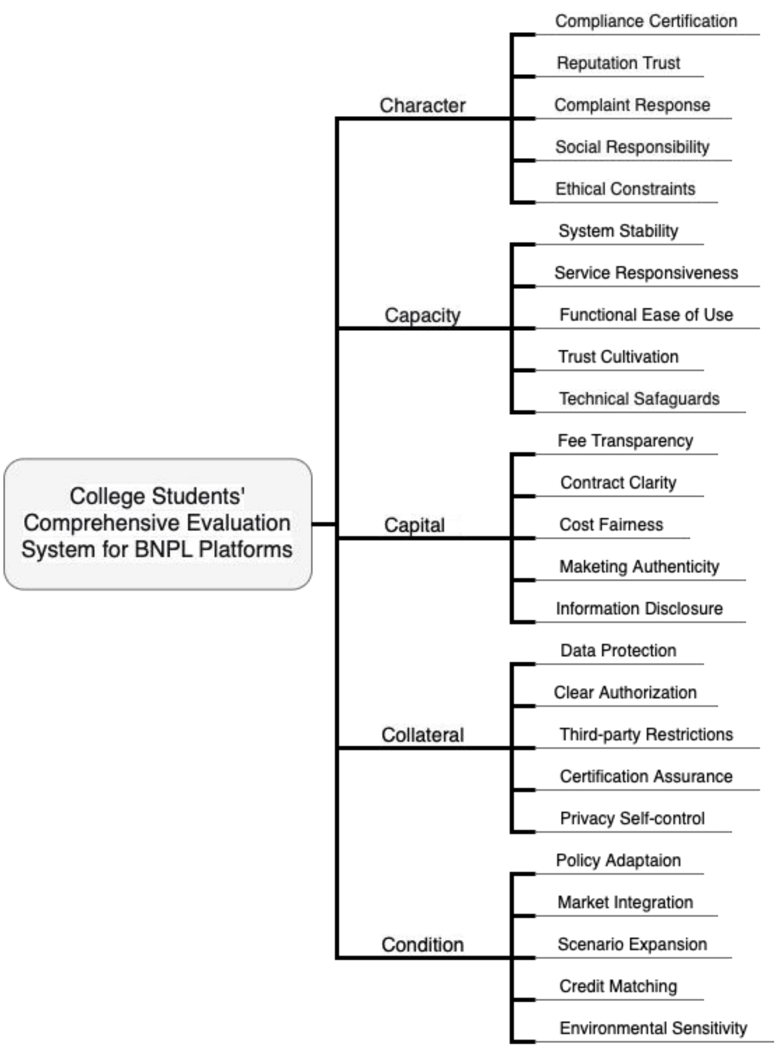

Figure 1 College Students' Comprehensive Evaluation System for BNPL Platforms

3.2 Questionnaire Development

To collect systematic data on college students' decision-making preferences regarding BNPL platform selection, this study primarily employed questionnaire surveys as the primary research tool. The questionnaire design strictly adhered to the theoretical foundations and practical application standards of AHP, ensuring both the completeness of measurement dimensions and the reliability of data collection. The questionnaire comprises three core sections:

Module 1: This study focuses on the respondents 'demographic characteristics and BNPL usage patterns, including gender, education level, monthly income distribution, and the adoption of Huabei (Ant Group's flagship installment payment service) and other credit tools. These variables not only characterize the sample population but also help identify variations in user preferences.

Module 2: This study employs AHP for empirical research, utilizing a pairwise comparison model to establish criterion and sub-criterion layers for quantitative evaluation. Following Saaty's (1990) 1-9 scale theory, pairwise comparisons are conducted across hierarchical elements. At the criterion level, ten evaluation criteria are established for five core dimensions: character, capability, capital, collateral, and condition, requiring respondents to specify their relative importance. Each sub-criterion is further refined through detailed comparison tasks. For the character dimension—including compliance certification, reputation trust, complaint handling, social responsibility, and ethical constraints—respondents complete ten pairwise comparison tasks. Similar procedures apply to other subfields such as capability, capital, collateral, and condition. The AHP method constructs an evaluation system comprising 60 pairwise comparisons, with each indicator supported by detailed quantitative standards and operational guidelines. This ensures respondents accurately understand the criteria's essence, thereby collateral the authenticity and reliability of evaluation data.

Module 3: Validity Check Items, designed to identify and exclude invalid samples to ensure data quality. Specifically, Question 9 ("What question does this study aim to explore?") evaluates respondents' comprehension of the research topic, while Question 13 ("Please indicate whether you agree with the following statement") serves as a standard attention check. These two questions are critical in data preprocessing.

3.3 Data Collection

To identify the key drivers for Chinese university students to choose BNPL platforms, this study adopted a stratified quota sampling method for data collection. The sampling frame was limited to in-school students who had used Huabei or other similar BNPL services within the past month, with cross-quotas set for educational background (associate degree/bachelor's degree/graduate/doctoral degree) and BNPL usage status (ongoing users/stopped users/potential demanders/never tried but interested) to ensure diversity and representativeness of the sample in key attributes.

Data collection was conducted through the Wenjuanxing online platform, which screened target populations from a national database of registered university students based on predefined quotas. Questionnaires were distributed via in-site messages and app notifications. The survey was conducted from October 28 to November 1, 2025, with 393 valid responses collected. Following rigorous data cleaning standards, 93 invalid questionnaires were excluded due to incorrect key item responses, patterned answers, or failure to pass the embedded question (Question 13), resulting in 300 valid responses with a 76.3% response rate. The AHP core methodology involved 60 pairwise comparisons, maintaining a valid sample size (N=300) to item ratio of 5:1 – a ratio consistent with established AHP research practices and deemed sufficient to ensure data stability and analytical reliability (Ho & Ma, 2018). This study protocol was approved by the institutional ethics committee, with all participants completing the survey after informed consent.

Summary: This chapter provides a detailed exposition of the research methodology. Building upon the reconstructed 5C model, we developed a three-tier AHP evaluation framework comprising target, criterion, and solution layers, establishing a theoretical foundation for quantifying college students' preferences toward the BNPL platform. In accordance with AHP methodology, we designed a structured questionnaire incorporating demographic data, pairwise comparison matrices, and validity check items as the primary tool for empirical data collection. This comprehensive research protocol lays a robust foundation for subsequent data gathering and analysis.

4. ANALYSIS:

Building upon the research methodology established in 3. Research Method, this chapter integrates the theoretical framework with empirical data to quantify the weightings of the BNPL platform evaluation index system using AHP. The study first determines the weights of indicators at each level through calculation of judgment matrices and consistency checks. Subsequently, systematic analysis of the weight results reveals the cognitive structure and risk preferences of university students when evaluating the BNPL platform. This ultimately enables the assessment and interpretation of the overall risk awareness level among this demographic.

4.1 Sample Analysis

The demographic characteristics of the valid sample are as follows: Gender distribution: 201 males (67.0%) and 99 females (33.0%); Educational background: 203 undergraduates (67.7%), 78 college graduates (26.0%), 16 master's degree holders (5.3%), and 3 doctoral candidates (1.0%); Monthly disposable income: 1,501-3,000 yuan for 160 individuals (53.3%), 3,001-5,000 yuan for 111 individuals (37.0%); BNPL usage status: 139 active users (46.3%), 66 former users (22.0%), 66 considering adoption (22.0%), and 29 never users with intention (9.7%). The study sample covers fundamental demographic features and BNPL usage patterns, demonstrating sufficient diversity and representativeness to serve as a valid basis for in-depth analysis. Although imbalances in gender and educational background (e.g., higher proportion of males and undergraduates) exist, this structural characteristic reflects partial realities of the target group. While limiting the generalizability of conclusions, it does not compromise the analytical validity of the core research question regarding college students' cognitive preferences toward BNPL platforms.

4.2 Weight Calculation and Consistency Check

This paper aims to transform the subjective evaluation of college students into quantitative weights. By using the mathematical modeling technique of AHP, the judgment matrix is created, the characteristic vector is solved and the consistency test is carried out, so that the weights with scientific basis and high reliability can be obtained. The technical principle and operation steps of this method are described in detail in the following.

(1) Calculate the weight vector: Use the geometric mean method to determine the relative weights of each indicator. First, compute the geometric mean of each element in the judgment matrix:

$$w_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} / \sum_{i=1}^{n} a_{ij} \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \qquad \text{equation 1}$$

a_{ij} denotes the relative importance scale of indicator $_i$ compared to indicator $_j$, and matrix A satisfies the positive reciprocity property of $a_{ij}=1/a_{ij}$.

(2) Determine the maximum eigenvalue λmax: To verify the consistency of the judgment matrix, its maximum eigenvalue must be calculated.

$$\lambda_{max} = \frac{1}{n}\left(\frac{w'_1}{w_1} + \frac{w'_2}{w_2} + \ldots + \frac{w'_n}{w_n}\right) \qquad \text{equation 2}$$

w'_i denotes the $_i$ component of the vector w'.

$$\begin{bmatrix} 1 & A_{12} & \ldots & A_{1n} \\ 1/A_{12} & 1 & \ldots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/A_{1n} & 1/A_{2n} & \ldots & 1 \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_3 \end{bmatrix} = \begin{bmatrix} w'_1 \\ w'_2 \\ \vdots \\ w'_3 \end{bmatrix} \qquad \text{equation 3}$$

(3) Consistency test: to ensure the logical consistency of the decision maker's judgment, consistency test is needed. First, calculate the Consistency Index (C.I.):

$$C.I = \frac{\lambda_{max} - n}{n-1} \qquad \text{equation 4}$$

Refer to the table7 below for the average Random Index (R.I.) (Saaty, 1990):

Table 7 Average Randomized Index of Consistency (R.I.) Standard Value

Matrix order (n)	1	2	3	4	5	6	7	8	9
R.I.	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

The consistency ratio (C.R.) is calculated as follows:

$$C.R. = \frac{C.I}{R.I} \qquad \text{equation5}$$

According to the consistency test criterion of Saaty (1990), if the relative consistency ratio CR of the judgment matrix is less than 0.10, the judgment matrix can be considered as having high credibility and the weight vector can be extracted.

4.3 Consistency Test Analysis:

To evaluate the consistency of the judgment matrix, this study adopted Saaty's (1990) method, using the CR as the primary assessment metric. This metric determines whether the matrix meets the predefined standard (CR <0.1); if exceeding this threshold, adjustments to the matrix structure or data are required. The calculation results indicate that all levels (including the criterion layer and five solution layers) in this study achieved CR values below 0.1, demonstrating that all judgment matrices passed the consistency test with errors within an acceptable range.

Based on the theoretical framework outlined above, this study employs the Analytic Hierarchy Process (AHP) to construct a model, deriving characteristic vectors (weights) for each hierarchical level to elucidate college students' cognitive preferences toward the BNPL platform. Table 8 presents the weight distribution of primary indicators at the criterion level, while Table 9 details the specific weight data for secondary indicators (character) at the solution level. Table 10 provides the validity statistics for the six matrices.

Table 8 Judgment Weights of First-Level Indicators in the Criterion Layer

	Character	Capacity	Capital	Collateral	Condition	Weight
Character	1.0000	2.8700	2.1096	1.7461	1.5649	0.3291
Capacity	0.3484	1.0000	2.0061	1.8341	1.8259	0.2226
Capital	0.4740	0.4985	1.0000	1.8477	1.9661	0.1821
Collateral	0.5727	0.5452	0.5412	1.0000	1.7628	0.1474
Condition	0.6390	0.5477	0.5086	0.5673	1.0000	0.1187

Table 9 Judgment Matrix of Second-Level Indicators (Character Dimension)

	Compliance Certification	Reputation Trust	Complaint Response	Social Responsibility	Ethical Constraints	Weight
Compliance Certification	1.0000	2.3142	1.5002	1.6443	1.3896	0.2903
Reputation Trust	0.4321	1.0000	2.0444	1.8043	1.6972	0.2341
Complaint Response	0.6666	0.4891	1.0000	1.7142	1.7845	0.1917
Social Responsibility	0.6081	0.5542	0.5834	1.0000	1.8565	0.1568
Ethical Constraints	0.7196	0.5892	0.5604	0.5387	1.0000	0.1272

Table 10 Matrix Validity Statistics Table

	Indicator Name	λmax	C.I.	C.R.
First-Level Indicators	5C	5.3033	0.0758	0.0677
Second-Level Indicators	C1 Character	5.2591	0.0648	0.0578
	C2 Capacity	5.1959	0.0490	0.0437
	C3 Capital	5.2295	0.0574	0.0512
	C4 Collateral	5.1859	0.0465	0.0415
	C5 Condition	5.3026	0.0757	0.0675

Based on the AHP weight assignment and consistency test, the data analysis results of college students' preferences for BNPL platform in this study can be summarized as:

The weight distribution across evaluation dimensions exhibits distinct hierarchical characteristics. Based on the importance of core indicators and their assigned weights, a descending sequence emerges: Character (0.3291)> Capacity (0.2226)> Capital (0.1821)> Collateral (0.1474)> Condition (0.1187). This weight allocation pattern reveals the value orientation and priority order in students' decision-making psychology when selecting BNPL platforms.

This study focuses on quality orientation, where the endogenous driving factors primarily originate from institutional signals. In this context, student groups place greater emphasis on specific verifiable information transmission pathways. The importance weights of secondary indicators, ranked from highest to lowest, are: Compliance Certification (29.03%)> Reputation Trust (23.41%)> Complaint Response (19.17%)> Social Responsibility Practices

(15.68%)> Ethical Norm Constraints (12.72%). The dimensions of capability and capital highlight the critical roles of operational convenience and cost transparency. From the capability perspective, system stability (0.2922) and service responsiveness (0.2274) are key technical factors supporting user trust. Regarding capital, students prioritize Fee Transparency (0.3175) and contract clarity (0.2334), which significantly outweigh considerations like marketing promotion or information comprehensiveness. The overall weight of the collateral and condition dimensions is relatively low, with concentrated internal focus. Data shows students generally pay insufficient attention to these two dimensions. Specifically, in the collateral dimension, data security (0.3272) is the core concern. In the condition dimension, policy adaptability (0.3318) is significantly more important than market factors like scenario integration and credit matching. The weight distribution reveals that students prioritize avoiding immediate and direct risks, while showing limited attention to long-term structural hazards like data privacy protection. Although they acknowledge the importance of these risks conceptually (e.g., data security accounts for 0.3272 of the total weight), their actual decision-making reflects insufficient emphasis, as evidenced by the platform's total weight of 0.1474. The study indicates a cognitive bias in students' risk perception: they focus on short-term policy risks while neglecting long-term concerns such as data security and platform sustainability. This cognitive pattern results in inadequate defense against potential strategic threats, highlighting a significant gap in their risk prevention capabilities.

This study employs quantitative analysis to construct a structural model of college students' cognitive evaluation of BNPL platforms. The model identifies platform credibility and functional attributes as foundational trust elements, with capital disclosure transparency serving as the core decision-making criterion. It also reveals students' relatively low attention to external collateral mechanisms and macroeconomic fluctuations. Using AHP ,this chapter quantitatively examines students' behavioral preferences in evaluating BNPL platforms. Through reliable judgment data and rigorous weight calculations, the research uncovers a cognitive model where students primarily base their decisions on immediate trust factors like character and capability, along with capital transparency, while showing limited concern for external collateral and macroeconomic conditions. This "experience-driven" pattern not only reflects the insufficient data security awareness among this demographic but also provides theoretical foundations for subsequent policy formulation.

5. CONCLUSION

This study innovatively develops the traditional 5C credit evaluation theory into a user-centric trust assessment system tailored for BNPL platforms. It quantitatively explores decision-making preferences using the AHP method. The key conclusions, validated through empirical data analysis, are summarized as follows:

This study constructs a trust framework centered on experiential cognition. University students 'evaluation of BNPL platforms demonstrates distinct characteristics of intuitive perception and instant feedback. Key factors like compliance, brand reputation, system stability, and service responsiveness carry significant weight, serving as primary drivers of short-term trust. Notably, when lacking sufficient financial knowledge, young users tend to assess potential risks and credibility through "surface-level indicators" such as interface friendliness and operational convenience. The research highlights the pivotal role of cognitive costs in consumer decision-making. From a capital perspective, students' heightened sensitivity to fee transparency and contract clarity reveals unique psychological patterns in digital credit selection: compared to specific interest rates, they exhibit greater sensitivity to uncertainty and are willing to pay a premium for clear regulatory information—primarily to mitigate risks arising from information asymmetry. The study identifies structural cognitive gaps, with lower emphasis on collateral and condition dimensions. This indicates that students often underestimate long-term credit constraints when their personal data serves as "digital collateral," while overlooking systemic risks from macro-regulatory policies and market fluctuations. The "sensitivity to short-term risks versus insensitivity to long-term risks" cognitive structure leaves students particularly vulnerable to complex, non-immediate structural risks.

The main theoretical contribution of this study is to fully expound and prove the action choice mechanism of college students in digital credit scenarios, which is based on "experience" and "cognitive cost", and to analyze the hidden limitation phenomenon in the two aspects of data privacy protection and macroeconomic risk control.

6. RECOMMENDATIONS:

The study's findings highlight two key issues among university students when evaluating BNPL platforms: their experience-driven cognitive preferences and insufficient attention to long-term structural risks. To effectively address these challenges, the research proposes targeted recommendations for higher education institutions, BNPL platforms and fintech companies, as well as regulatory authorities.

6.1 Recommendations for higher education institutions

As outlined in 5.Conclusion, evaluations of BNPL platforms by university students demonstrate a "experience-driven trust framework" with structural gaps in risk awareness. To address this, higher education institutions must integrate systematic digital finance risk education into their talent development systems. The curriculum should expand beyond traditional savings and investment concepts, providing in-depth analysis of technical mechanisms, actual cost structures, and the long-term binding force of data privacy clauses in innovative credit products like BNPL. Educational objectives should prioritize cultivating students' critical thinking and risk identification skills, including: analyzing annualized interest rates (APR) and actual fees, understanding compound interest effects in revolving credit, and evaluating potential risks in data authorization agreements. Teaching methodologies should adopt interactive practices such as case studies, scenario simulations, and real-bill analysis to help students develop long-term financial planning perspectives and solid data privacy awareness in practical contexts, thereby addressing structural deficiencies in risk cognition.

6.2 Recommendations for BNPL Platform and Fintech Enterprises

The study conclusively demonstrates that students' decision-making prioritizes "cognitive cost" in consumption choices, showing heightened sensitivity to fee transparency and contract clarity, and being willing to pay premiums to mitigate information asymmetry risks. Based on these findings, platforms and businesses should focus on building trust systems centered on transparency and user-centric care. First, they must achieve absolute transparency in key information like fee structures and penalty interest rates, displaying annualized interest rates through unified and prominent displays to prevent critical terms from being overshadowed by lengthy agreements. Second, product designs should embody responsible finance principles by optimizing authorization processes to avoid "one-stop" bundling, while introducing personalized repayment reminders and grace period settings to reduce irrational debt risks through systemic measures. Finally, establishing efficient and fair online dispute resolution channels, along with proactive notification and communication obligations during sensitive events like credit adjustments or transaction anomalies, is crucial for enhancing user control and building long-term mutual trust.

6.3 Recommendations for regulatory and policy-making bodies

The study reveals that students generally exhibit a "near-field risk sensitivity with long-term risk insensitivity" pattern, focusing on short-term policy risks while overlooking long-term concerns like data security and platform sustainability. This cognitive bias in risk prevention necessitates external governance measures from regulators. Regulatory frameworks should transition from the traditional capital adequacy-centric model to precise governance of behavioral risks and systemic vulnerabilities. It is recommended to incorporate principles of algorithmic fairness, data usage legitimacy, and user consent integrity into existing frameworks, while increasing the weight of conduct supervision. Technologically, a tiered monitoring and early warning system based on platform behavioral risks should be established, utilizing regulatory technology to dynamically track marketing practices, pricing strategies, and customer complaints for targeted interventions. Furthermore, regulators should adopt a forward-looking perspective, prioritizing credit accessibility for youth groups, the social spillover effects of punitive fees such as late payment penalties, and potential social exclusion risks from algorithmic credit assessments, thereby preventing individual risk accumulation from escalating into systemic societal risks.

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