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Gender differences in library book borrowing volume: The influence of psychological variables and temporal moderation

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Abstract

This study explores gender differences in library book borrowing with psychological variables and temporal moderation. Using PCA, SEM, logistic regression, and 2SLS, it analyzes reading preferences and borrowing behaviors. Females dominate literature and social science borrowing, while males prefer military, transportation, and STEM materials. SEM shows moderate factor suitability (KMO: 0.683 for males, 0.659 for females), with distinct structures: males have a three-factor model, and females a two-factor model. Logistic regression reveals a temporal decline in total borrowing volume's positive effect on renewal behavior, with significant volume-time interactions ($p < 0.001$). 2SLS confirms that predicted variables from time, psychological factors, and renewal behavior influence borrowing volume differently by gender. The findings highlight the complex interplay of gender, psychology, and time in library usage, guiding resource allocation and gender-specific services.

Keywords:
Book borrowing
Gender differences
Logistic regression
Psychological variables
Structural equation modeling
Temporal moderation.

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1. Introduction

The examination of gender disparities in library book borrowing volumes intersects with broader discussions regarding the influence of sociocultural constructs and psychological variables on human behavior. This introduction situates the inquiry within the frameworks of gender studies, reading behavior, and temporal dynamics, underscoring the necessity of addressing both psychological drivers and contextual moderators.

A fundamental distinction between biological sex and sociocultural gender is pivotal for comprehending variations in borrowing patterns (Shapiro, 2019). Gender roles, acquired through cultural socialization, significantly dictate behavioral expectations, including preferences in reading and library utilization (Shapiro, 2019). For instance, the historical association of women with caregiving roles may contribute to a propensity for borrowing family-oriented or educational materials, while men's predominance in technical fields could engender a preference for texts related to STEM (Sibirskaya, 2022). Psychologically, the "male hubris, female humility effect" (Reilly, Neumann, & Andrews, 2022) posits that men's overconfidence in their cognitive abilities may lead to a more assertive engagement with complex texts, whereas women's socialized modesty could result in more selective genre choices. These dynamics are reinforced by prevailing societal norms, such as wage disparities and underrepresentation of women in leadership positions (Sibirskaya, 2022) which may indirectly shape reading priorities related to career advancement and personal development.

Empirical research consistently reveals gender-based disparities in reading habits. Women often exhibit a preference for fiction genres, particularly romance and horror, whereas men tend to gravitate towards non-fiction and science fiction (Ramasamy & Padma, 2020). These preferences extend to formats, as women engage more with print and online materials, while men show a preference for e-readers and digital platforms (Liu & Huang, 2008; Tveit & Mangen, 2014). Such differences may reflect broader gaps in technological comfort, where men's higher self-efficacy in computer use (Kim, 2010) facilitates the adoption of library digital tools more readily, in contrast to women's reliance on user-friendly interfaces (Kim, 2010) which may inhibit exploration of more complex resources. In library contexts, gender roles manifest in patterns of service usage: women are more likely to frequent general collections and family areas, while men prioritize electronic resources and business-related materials (Adetayo, 2024). Additionally, older women's technophobia can exacerbate disparities in digital access (Dixon et al., 2014) illustrating how the intersection of age and gender shapes borrowing behavior. Furthermore, adolescents often perceive libraries as "female-friendly" for their personal information needs (Agosto, Paone, & Ipock, 2007) suggesting that early socialization influences enduring patterns of library engagement.

Temporal factors introduce an additional layer of complexity. The fragmented schedules often experienced by women, due to caregiving responsibilities (Jiao, Li, & Liu, 2021) may lead to a reduction in borrowing frequency or a preference for shorter-form materials, whereas men's more structured approach to time (Aeon, Faber, & Panaccio, 2021) supports consistent engagement with longer texts. Historical analyses indicate that women tend to overestimate time intervals (Koglbauer, 2015) potentially impacting their book return habits; however, modern shifts in gender roles have rendered this relationship less predictable. Age also interacts with gender: younger adults often borrow more frequently for educational purposes, while older women may experience a decline in borrowing due to technophobia or reduced physical mobility (Lisenkova & Shpagonova, 2021).

Cultural norms further mediate temporal behaviors related to library usage. For example, the American emphasis on punctuality (Agranovich, Melikyan, & Panter, 2021) may promote timely book returns, whereas collectivist cultures might prioritize communal reading spaces over individual borrowing. Interventions, such as time management training (Häfner & Stock, 2010) could enhance borrowing consistency; however, they must address gender-specific challenges, such as caregiving responsibilities for women or work-centric schedules for men. Psychological constructs, including self-esteem and stereotype threat, play critical roles in influencing borrowing behavior. Men's propensity to overestimate their intelligence (Reilly et al., 2022) may promote risk-taking in genre selection, particularly with technical or philosophical texts, whereas women's lower self-assessment of competence in STEM fields (Pettitt, 2004) could deter borrowing in these domains. Furthermore, children's internalization of reading stereotypes (Chapman, Filipenko, McTavish, & Shapiro, 2007) such as boys favoring informational texts and girls gravitating towards narratives, reinforces enduring patterns of reading behavior, highlighting the necessity for early intervention strategies.

Libraries face significant challenges in addressing these disparities. For example, the observed lag in electronic resource utilization among women (Steinerová & Šušol, 2007) underscores the urgent need for targeted digital literacy workshops, while men's reluctance to engage with "feminized" genres, such as romance, emphasizes the importance of creating inclusive displays that challenge prevailing stereotypes (Merga, 2017). Failure to address these disparities perpetuates unequal access to information, thereby limiting women's economic self-sufficiency (Pettitt, 2004) and men's emotional literacy. While existing literature addresses genre, format, and cultural influences, few studies integrate psychological variables (e.g., self-efficacy, motivation) with temporal moderators (e.g., life stages, seasonal borrowing) to explain borrowing volume. This study fills this gap by examining how gender interacts with factors like reading motivation and time perception to shape library usage over time. By analyzing borrowing data across age groups and cultural contexts, we aim to identify strategies for promoting equitable engagement, such as gender-sensitive resource promotion and flexible borrowing policies.

The research questions of this study include the following five aspects:

1.1. Gender Differences and Driving Factors in Library Borrowing Behaviours Across Different Pandemic Phases

Q1: Between 2016–2024, did significant differences exist in book borrowing volume, renewal behavior, and reading preferences between male and female users across the pre-pandemic, pandemic-impact, and post-pandemic recovery phases?

Q2: What underlying factors drive these gender differences? How do user types (undergraduate, postgraduate, faculty/staff), log-transformed borrowing volume (LogTotal), and latent factors extracted via Principal Component Analysis (e.g., F1, F2, F3) moderate the relationship between gender and borrowing behaviors?

1.2. Influencing Factors of Renewal Behaviour and Their Temporal Variations

Q3: Which factors (e.g., borrowing volume, user type, pandemic phase, latent factors) significantly impact renewal behavior (renewed/non-renewed)?

Q4: Do the effects of these factors change dynamically over time (pre-pandemic, pandemic, post-pandemic)? For instance, did the positive effect of borrowing volume on renewal weaken during the pandemic?

1.3. Structural Differences in Latent Borrowing Patterns Between Genders

Q5: What borrowing patterns do the latent factors identified via PCA (e.g., three-factor structure in male samples, two-factor structure in female samples) reflect?

Q6: Why do gender-specific factor structures exist (e.g., Factor F3 in males linked to military/transportation books, Factor F1 in females linked to humanities/social sciences)? Are these differences associated with sociocultural factors influencing gendered reading preferences?

1.4. Explanatory Power of Standardized Predicted Values (ZPR_1) Vs. Individual Factors

Q7: Does the standardized predicted value (ZPR_1), which integrates multiple latent factors, explain borrowing volume more effectively than individual factors (e.g., F1, F2, Time)?

Q8: In Two-stage Least Squares (2SLS) models, do regression coefficients and model fit metrics (e.g., R^2) for ZPR_1 significantly exceed those for individual factors? What methodological implications does this have for modeling library user behaviors?

1.5. Long-Term Impact of the Pandemic on Library User Engagement

Q9: Did user borrowing volume, renewal rates, and reading preferences differ significantly during the pandemic phase (2019–2021) compared to pre- and post-pandemic phases?

Q10: Does the negative correlation between the Time variable and engagement metrics (borrowing volume, renewal rate) indicate a decline in post-pandemic user engagement? Which factors (e.g., F2, user type) might mitigate or exacerbate this trend?

To address these complex issues, it is essential to engage in a multidisciplinary approach that incorporates insights from sociology, psychology, education, and library science. This inquiry will explore the nuances of gendered experiences in library environments, aiming to uncover not only the disparities but also the factors that may facilitate more equitable borrowing practices. By identifying effective strategies to mitigate existing biases and barriers, libraries can enhance their roles as inclusive spaces for learning and literary exploration, ultimately empowering all patrons to engage fully with the wealth of knowledge available to them.

2. Previous Research

2.1. Theoretical Foundations of Gender Differences

The study of gender differences in library book borrowing must first anchor in the theoretical distinction between biological sex and sociocultural gender. Hossain (2024) and Shapiro (2019) emphasize that while sex denotes biological traits, gender is a dynamic social construct shaped by cultural norms and power structures. This framework is critical, as it highlights how societal expectations, such as assigning caregiving roles to women (Hossain, 2024) systematically influence behavior, including reading and library use. For instance, women's historical marginalization in STEM fields (Sibirskaya, 2022) may correlate with lower borrowing of technical literature, while gender stereotypes about emotional labor could drive women toward humanities genres (Pettitt, 2004). Notably, the "male hubris, female humility effect" (Reilly et al., 2022) suggests men's overestimation of cognitive abilities might translate to more confident engagement with complex texts, whereas women's socialized modesty could lead to genre choices aligned with perceived cultural appropriateness. However, Heavey (2024) work on health behaviors underscores that gender norms are not static; interventions challenging biases (Tomar, Dowlath Nisha, Kandasamy, & Rathore, 2024) may reshape borrowing patterns over time.

2.2. Gendered Patterns in Reading Behaviour

Empirical research consistently documents genre and format preferences as significant dimensions of gender-related variations in reading behavior. Studies indicate that girls and women display a pronounced preference for fiction genres, particularly romance and horror (Loh, Sun, & Majid, 2020; Ramasamy & Padma, 2020) while men tend to gravitate toward non-fiction, science fiction, and technical texts (Thelwall, 2019). This observation aligns with emotional labor theory, positing that women often engage with reading as a means of fostering empathy and managing relationships, in contrast to men's goal-directed pursuit of information (Thums, Artelt, & Wolter, 2021). Moreover, format choices further illuminate gendered interactions with technology: women typically demonstrate a preference for print media but utilize online materials for their convenience (Liu & Huang, 2008) whereas men's higher self-efficacy in computer use (Kim, 2010) encourages the adoption of e-readers and digital platforms (Tveit & Mangen, 2014). Such disparities may be exacerbated in library contexts, where men's comfort with digital resources (e.g., library websites) contrasts with potential technophobia among women, particularly among older patrons (Dixon et al., 2014).

2.3. Temporal Dynamics and Time Management

Time-related variables significantly influence borrowing behavior, particularly regarding gender. Women's fragmented schedules, often impacted by caregiving responsibilities (Jiao et al., 2021) may inhibit sustained engagement with long-form texts. Conversely, men's more structured approach to time management (Aeon et al., 2021) appears to support consistent borrowing patterns. Koglbauer (2015) observes that women's historical tendency to overestimate time intervals could affect their return habits; however, contemporary shifts in gender roles have complicated this trend. Lisenkova and Shpagonova (2021) illuminate age-gender interactions in borrowing behavior, revealing that younger women tend to borrow more frequently during educational stages, while middle-aged men exhibit stabilized borrowing patterns in alignment with professional commitments. Libraries could capitalize on the findings by Häfner and Stock (2010) which indicate that time management training enhances user engagement, by offering flexible borrowing options or digital micro-content tailored for individuals with irregular schedules.

2.4. Library Usage and Psychological Factors

Psychological constructs like self-efficacy and stereotype threat deeply influence library behavior. Men's higher computer self-efficacy (Kim, 2010) correlates with greater use of online catalogs and research databases, while women's preference for user-friendly interfaces (Kim, 2010) may limit exploration of complex digital tools. Agosto et al. (2007) observe that adolescents perceive libraries as "female-friendly" for personal information needs, potentially shaping lifelong borrowing habits. Social norms also play a role: men's avoidance of "feminized" genres (e.g., romance) and women's hesitation with "masculine" topics (e.g., military history) reflect internalized stereotypes (Chapman et al., 2007). Libraries can mitigate this through inclusive displays (e.g., cross-genre recommendations) and targeted programs, such as digital literacy workshops for women (Steinerová & Šušol, 2007) and genre-bending reading lists to challenge assumptions (Merga, 2017).

2.5. Gaps and Future Directions

While existing literature addresses genre, format, and time, fewer studies explore the interplay of psychological variables (e.g., self-esteem, motivation) and temporal moderators (e.g., life stages, seasonal borrowing patterns). For example, how does career transition (e.g., maternity leave, retirement) alter borrowing volume differently for genders? Additionally, cross-cultural research is limited; do gender differences in borrowing persist in collectivist societies versus individualist ones (Hossain, 2024)? Interventions rooted in social cognitive theory (Bandura, 1986) could be tested, such as using male and female librarian role models to promote underrepresented genres. Longitudinal studies tracking borrowing over decades might reveal how aging and shifting gender norms reshape behavior, building on Lisenkova and Shpagonova (2021) lifespan insights.

Gender differences in library book borrowing are multifaceted, reflecting sociocultural norms, psychological predispositions, and temporal constraints. Libraries must adopt gender-sensitive strategies—from digital tool design to programming—to ensure equitable access. Future research should prioritize dynamic models that integrate psychological variables and temporal shifts, offering a more nuanced understanding of this complex phenomenon.

This research stands out for its longitudinal, gender-disaggregated analysis of library borrowing behaviors across distinct pandemic phases (pre-, during, and post-pandemic). Unlike most studies, it employs Principal Component Analysis (PCA) and Structural Equation Modeling (SEM) separately for male and female users, uncovering gender-specific latent factors in borrowing patterns—such as a three-factor structure for males (linked to military, transportation, and STEM disciplines) and a two-factor model for females (focused on humanities and social sciences). Additionally, the innovative use of Two-Stage Least Squares (2SLS) models tests the explanatory power of composite predictors (e.g., ZPR_1) versus individual factors, providing robust causal insights into how aggregated latent variables drive borrowing volume. This multi-method approach integrates quantitative data (borrowing metrics, renewal rates) with categorical variables (user type, book categories), offering a nuanced understanding of pandemic impacts on diverse user groups.

The study makes theoretical contributions by demonstrating that pandemic-related disruptions affect male and female users differently, with gender-specific factors influencing engagement and renewal behaviors. For library science, this highlights the need to account for social and disciplinary norms in modeling user behavior. Methodologically, it validates advanced causal inference techniques (e.g., 2SLS) as superior to traditional regression for explaining complex borrowing patterns. Practically, findings inform targeted library strategies: prioritizing STEM resources for male users, expanding humanities collections for females, and tailoring interventions to pandemic phases (e.g., boosting digital services during post-pandemic recovery). The research also underscores the importance of phase-specific policies to address declining engagement over time, such as leveraging factor scores (e.g., F3 for males) to identify at-risk groups. By combining rigor with real-world applicability, this study enhances our understanding of academic library dynamics in crisis contexts and provides a foundation for equitable, evidence-based resource management.

3. Data and Method

3.1. Data Collection and Preparation

Book borrowing data were collected from Nanjing Normal University's library information system, encompassing detailed records such as borrowing timestamps, user demographics (undergraduate, graduate, faculty/staff), book categories, and renewal status (whether the borrowing was renewed). Before analysis, missing values were systematically identified and removed via listwise deletion to ensure data integrity. The research design is shown in Figure 1.

3.2. Data Categorization and Grouping

3.2.1. Categorization Dimensions

The variables are categorized and assigned. Gender is classified into two categories with numerical codes: Male is assigned 1, and Female is assigned 2. Renewal Status includes two states: Non-renewed is labeled 0, and Renewed is labeled 1. Borrowing Volume undergoes a log transformation (base 10) to normalize its distribution, with the transformed values used in analysis. Periods are divided into three phases: 2016–2018 (pre-pandemic) assigned 1, 2019–2021 (pandemic-impact period) assigned 2, 2022–2024 (post-pandemic recovery) assigned 3. User Type consists of three groups: Undergraduate students are coded 1, postgraduate students 2, and faculty/staff 3.

3.2.2. Grouping

Borrowing records were stratified into distinct groups based on the above categories to facilitate comparative analysis of book borrowing behaviors across different demographics and temporal phases.

3.3. Data Analysis

3.3.1. Common Factor Extraction

PCA was applied to identify latent factors underlying borrowing patterns across user groups (undergraduates, postgraduates, faculty/staff) from 2016 to 2024. Data suitability for PCA was verified using the Kaiser-Meyer-Olkin (KMO) measure (requirement: KMO > 0.6) and Bartlett's Test of Sphericity (significance: $p < 0.001$). Varimax rotation was performed to enhance factor interpretability, retaining factors with eigenvalues > 1, factor loadings > 0.5, and at least three contributing variables. Extracted factor scores were standardized using Z-scores and incorporated as covariates in subsequent regression models.

3.3.2. Regression Analyses

3.3.2.1. Binary Logistic Regression

A binary logistic regression model was constructed to analyze factors influencing renewal behavior, with renewal status (Y variable; 0 = non-renewed, 1 = renewed) as the dependent variable. The model included standardized predicted values as the independent variable (X variable), gender as a moderator, and covariates such as period and user type.

3.3.2.2. Linear Regression

Concurrently, a linear regression model was employed with LogTotal (the natural logarithm of total borrowing volume) as the dependent variable, incorporating Z-score F1, Z-score F2, Z-score F3, and Time as independent variables via the Enter method. Coefficients from this model quantify the individual impact of each predictor on LogTotal. To address potential endogeneity or measurement error, predicted values from this regression were standardized and used as instrumental variables in a Two-stage Least Squares (2SLS) analysis. This approach isolates exogenous variation in the predictors: the first stage regresses standardized values onto endogenous variables to generate cleaned components, which are then used in the second stage to estimate causal effects, mitigating bias and enhancing robustness.

3.3.2.3. Linear Regression with Two-Stage Least Squares (2SLS)

To validate the hypothesis that Standardized Predicted Values (ZPR_1) yield stronger explanatory power than individual factors in predicting borrowing behavior, two Linear Regression with Two-stage Least Squares (2SLS) models were constructed and compared. Model 1 specified Log-transformed total borrowing volume (LogTotal) as the dependent variable, with Renewal, Reader type, and ZPR_1 as explanatory variables. Instrumental variables mirrored the explanatory set to address potential endogeneity. Model 2, designed for comparison, replaced ZPR_1 with granular factors: Time, Z-score F1, Z-score F2, and Z-score F3, while retaining Renewal and Reader type. The hypothesis was tested by contrasting: 1) the regression coefficients of ZPR_1 in Model 1 against those of individual factors (Time, Z-scores) in both traditional linear regression and their respective 2SLS models; 2) the statistical significance and effect sizes of these coefficients; and 3) overall model fit metrics (e.g., R^2, adjusted R^2). A higher magnitude and significance of ZPR_1's coefficient, coupled with improved model fit in Model 1, would support the assertion that ZPR_1, by integrating multiple latent factors, captures more comprehensive exogenous variation, thus offering a more robust explanation of borrowing volume than individual predictors alone.

This comprehensive research design integrates multi-dimensional data categorization, statistical modeling, and causal inference techniques to systematically examine disparities in library borrowing volumes, renewal behaviors, and reading preferences among different user groups before, during, and after the COVID-19 pandemic.

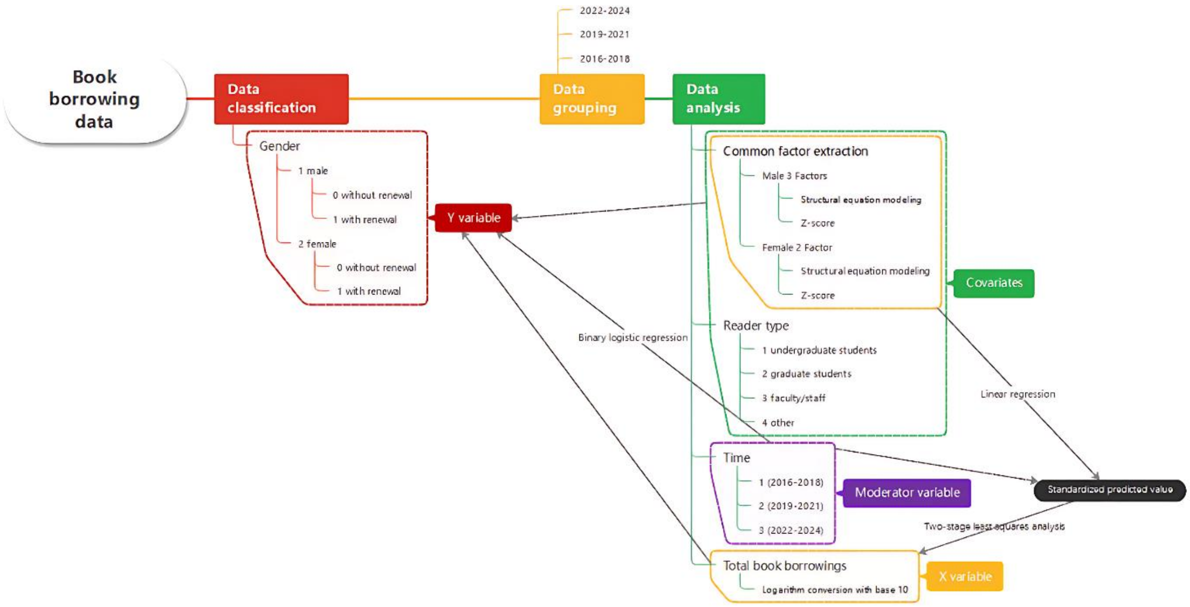

Figure 1. Research design.

4. Results

4.1. Total Book Borrowing Distributions

When examining the book borrowing distributions of women and men, notable differences emerge across several key aspects, as shown in Figures 2 and 3.

Overall Range and Extreme Values: In the graph for women's book borrowings, the range is quite extensive, with data points stretching from near 0 to approximately 1300. The outlier around 1300 has a significant impact. It indicates that at least one woman borrowed an unusually large number of books compared to her peers, making the distribution appear more dispersed and potentially distorting statistical measures such as the mean. In contrast, the second graph for men's book borrowings shows a range from close to 0 to 900. The outlier at 900 is less extreme in magnitude. This suggests that, generally, the upper limit of borrowing numbers for men is lower than that for women in this dataset, and the male borrowing distribution is more concentrated towards the lower end of the scale.

Central Tendency and Distribution Shape: Determining the median precisely without formal calculation is challenging, but for women, the central tendency, where most data clusters, seems to be in the lower - to - middle range, perhaps between 200 - 400. However, the high outlier pulls the mean upwards, making it higher than the typical borrowing number for most women. The distribution is skewed to the right because of this outlier. For men, the data points cluster more densely in the lower range, say below 400, and the median is likely in this lower range. The distribution is also somewhat skewed, but less so than women's, as the outlier has a relatively smaller impact on the overall shape due to its lower value. This shows that most men's borrowing behavior is more concentrated around lower numbers compared to women.

Frequency of Borrowing Levels: Among women, there is a wider variety of borrowing levels. Multiple data points are concentrated in the lower ranges, yet several are spread across higher levels before reaching the extreme outlier. This reflects greater diversity in the number of books women borrow, with some borrowing small amounts, some in the moderate range, and a few borrowing very large quantities. For men, the frequency of borrowing levels shows a greater concentration in the lower ranges. There are fewer data points in the higher borrowing levels compared to women, meaning men are more likely to borrow relatively small numbers of books, and fewer men borrow large quantities compared to women.

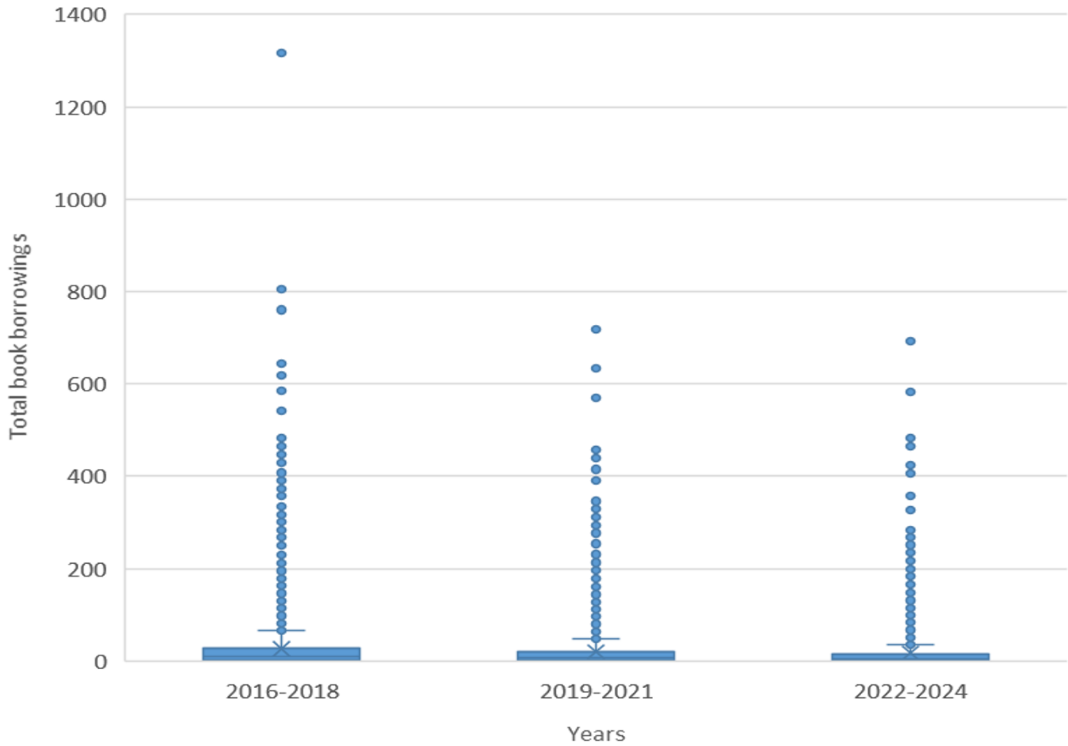

Figure 2. Total book borrowing distributions of females.

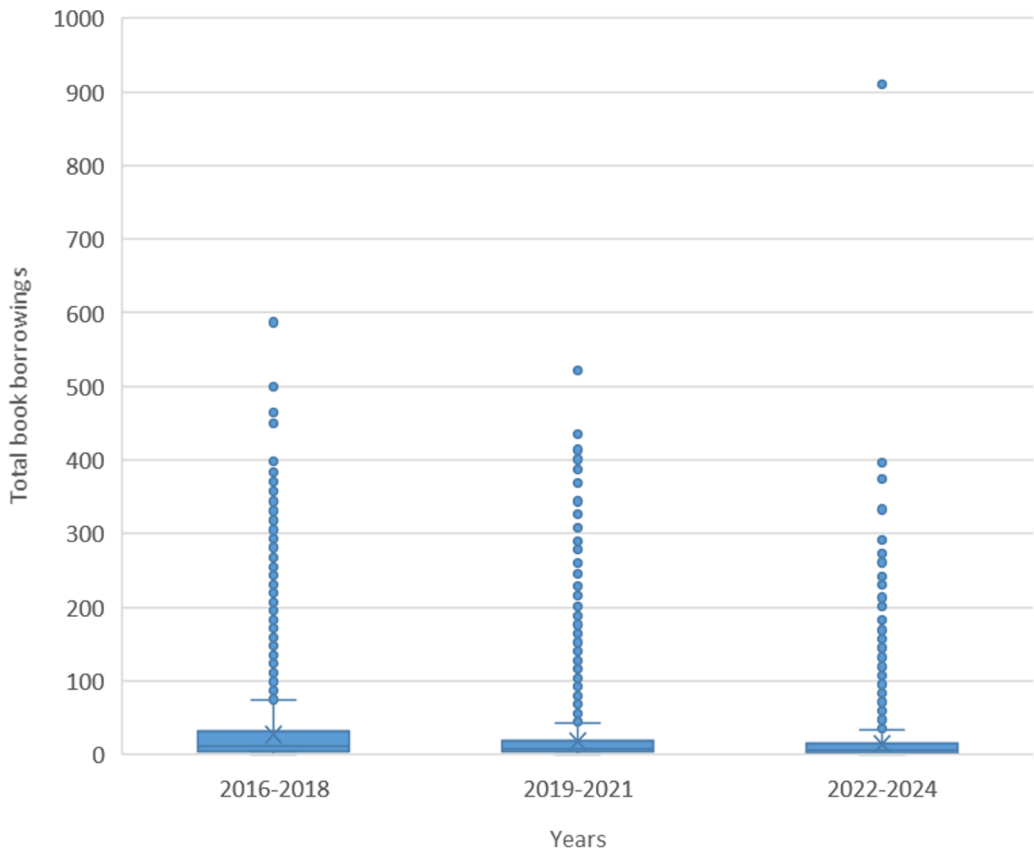

Figure 3. Total book borrowing distributions of males.

4.2. Reading Preference Comparison

As depicted in Figure 4, females (Represented by the orange segments) have a higher prevalence across most book categories. For instance, in categories such as A, B, and C, the orange portions of the bars are notably larger, signifying that women are more predisposed to reading materials within these areas. This trend suggests that females either possess broader reading interests or that certain commonly favored areas hold a particular allure. Conversely, men exhibit pronounced preferences in several distinct categories. In the E (Military) category, male readership surpasses that of females. This is likely because military-themed content, which includes military history, strategy, and equipment, strikes a chord with men's sense of adventure, patriotism, and their penchant for technical and strategic intricacies. Similarly, in the V (Transportation) category, males are more prevalent. Topics associated with transportation, like vehicle engineering, aviation, and shipping, entail technical know-how and engineering concepts that captivate men interested in mechanics, technology, and infrastructure. Furthermore, in science - related categories such as N (Natural Sciences), O (Mathematics, Physics, etc.), P (Astronomy, Geosciences), Q (Biology), R (Medical, Sanitary), S (Agriculture, Forestry), and T (Industry, Technology), men generally display a relatively stronger preference.

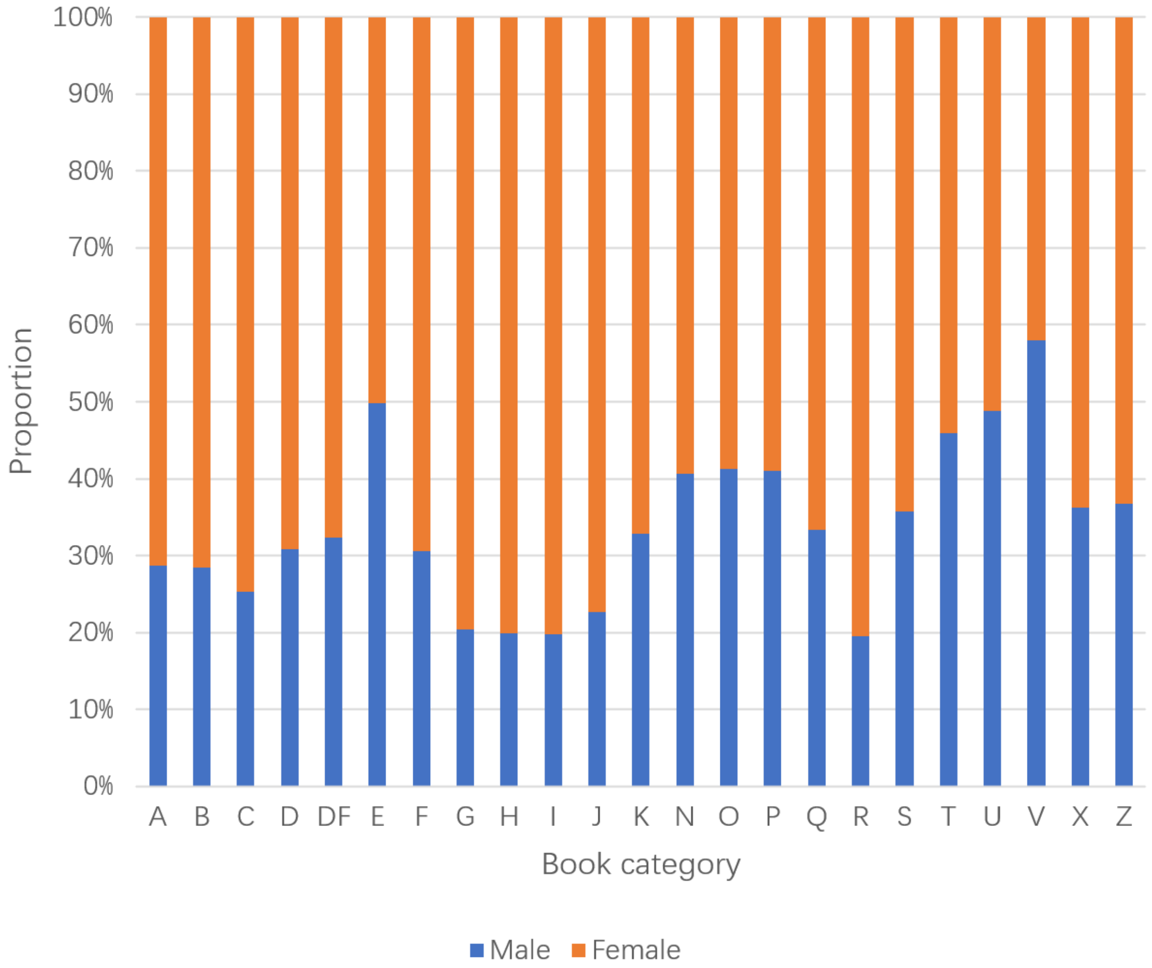

Figure 4. Gender comparison of book reading categories.

4.3. Factor Extracted

The structural equation model (SEM) analysis for the male sample in Figure 5 shows a KMO value of 0.683, indicating moderate suitability for factor analysis, while Bartlett's Test of Sphericity is highly significant ($p < 0.001$), confirming variable correlations suitable for factor analysis. All indicator variables significantly load onto their respective factors ($p < 0.001$), with core indicators like C (standardized loading = 0.872) and T (0.595) strongly influencing Factors 2 and 3, respectively. Factor correlations are low (0.049–0.283), supporting discriminant validity. However, Variable E shows extremely low variance explained (R^2= 0.015), suggesting misalignment with F3, while variables like I, Z, G, F, and O have weak loadings (<0.4), warranting item refinement. High error variances for some indicators indicate potential reliability issues. The covariance analysis reveals significant positive covariations between all factor pairs (F1↔F2=7.476, p<0.001; F3↔F1=0.660, p=0.001; F3↔F2=0.609, p<0.001), indicating non-random joint variability. Correlation coefficients show a moderate positive association between F1 and F2 (r=0.283), a weak positive link between F3 and F2 (r=0.130), and a near-zero correlation between F3 and F1 (r=0.049), supporting the distinctiveness of F3 as a separate construct while acknowledging some shared variance between F1 and F2.

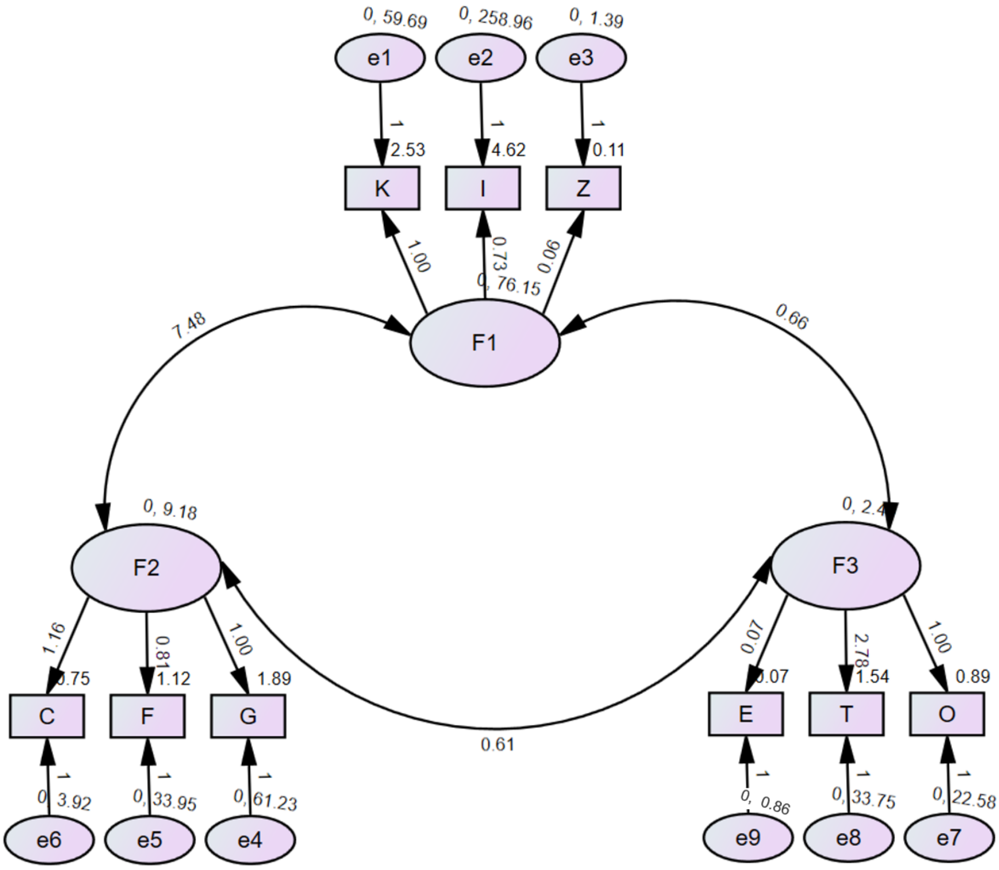

Figure 5. The structural equation model for the males.

The structural equation model (SEM) for the female sample in Figure 6 yields a KMO value of 0.659, indicating moderate suitability for factor analysis, while Bartlett's Test of Sphericity is highly significant ($p < 0.001$), confirming variable correlations suitable for factor analysis. The model supports a two-factor structure: F1 is primarily driven by Variable B (standardized loading = 0.584, R^2 = 34.1%), while F2 is strongest with Variable I (0.542, R^2 = 29.4%). However, Variable H in F2 shows weak convergence (R^2 = 6.8%), and high error variances for G and I suggest reliability issues. The moderate-to-strong correlation between F1 and F2 ($r = 0.590$) indicates related but distinct constructs, though the model's overall explanatory power is limited, with most indicators explaining less than 40% of variance.

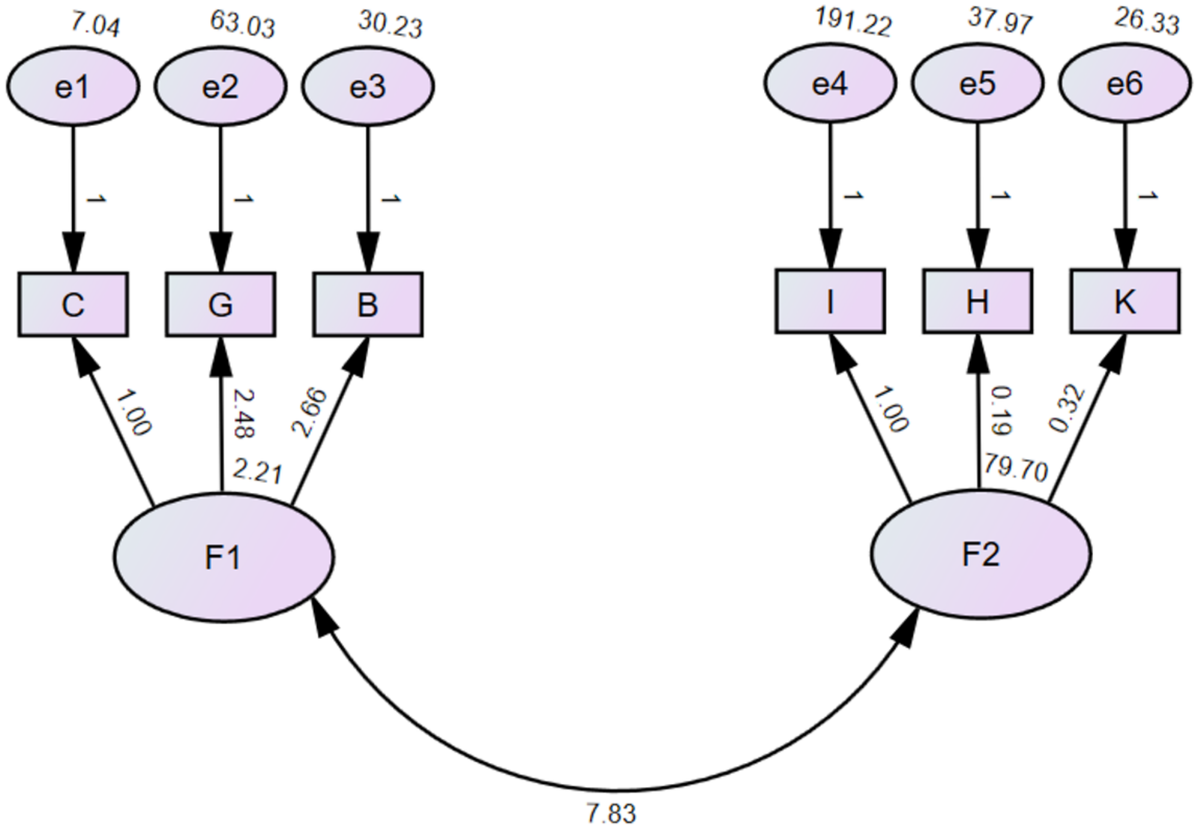

Figure 6. The structural equation model for the females.

4.4. Correlations

Table 1 presents the correlations among variables for a male sample with a size of 19,873. The correlation coefficients marked "**" signify significance at the 0.01 level (two-tailed test). Regarding Reader Type, it has a positive and significant correlation with Renewal (r = 0.150**), suggesting that different reader types have distinct renewal propensities. The relationship between Renewal and Time is negative and significant (r = -0.256**), indicating that as time elapses, renewal behavior is likely to decrease. LogTotal shows a notable positive correlation with Z-score F1 (r = 0.427**), highlighting a close link between the logarithm of total borrowing volume and the Z-score of F1. For Z-score F2, it also has positive and significant correlations with Reader Type (r = 0.101**), Renewal (r = 0.195**), and LogTotal (r = 0.356**). This implies that factor score F2 is related to reader categories, renewal actions, and the overall borrowing quantity in a positive manner. Z-score F3, on the other hand, has a relatively weak relationship with Reader Type (r = - 0.007, not significant), but a positive and significant correlation with Renewal (r = 0.112**) and LogTotal (r = 0.131**). This indicates that while it may not be strongly associated with reader type, it does have some positive connections with renewal behavior and the total borrowing volume. Notably, all correlations marked with ** are statistically significant at the $p < 0.01$ level (2-tailed), underscoring the reliability of these associations in the dataset.

Table 1. Correlations for males (N = 19,873).

Variables	Reader type	Renewal	Time	LogTotal	Z-score F1	Z-score F2	Z-score F3
Reader type	1	0.150**	0.025**	0.139**	0.060**	0.101**	-0.007
Renewal	0.150**	1	-0.256**	0.383**	0.199**	0.195**	0.112**
Time	0.025**	-0.256**	1	-0.130**	-0.046**	-0.066**	-0.043**
LogTotal	0.139**	0.383**	-0.130**	1	0.427**	0.356**	0.131**
Z-score F1	0.060**	0.199**	-0.046**	0.427**	1	0.000	0.000
Z-score F2	0.101**	0.195**	-0.066**	0.356**	0.000	1	0.000
Z-score F3	-0.007	0.112**	-0.043**	0.131**	0.000	0.000	1

Note: "**" indicates that the correlation coefficient is significant at the 0.01 level (Two-tailed test).

Table 2 presents the correlations among variables for a female sample with a size of 60,670. Positively, Renewal and LogTotal are strongly positively correlated (0.382**), a pattern consistent with the relationships observed in Table 1. LogTotal demonstrates a very strong positive association with Z-score: F2 (0.511**), indicating a close link between higher total values and the second factor score. Meanwhile, Z-score: F1 shows moderate positive correlations with Reader Type (0.117**) and Renewal (0.210**), suggesting moderate interdependencies with these variables. On the negative side, Time is significantly negatively correlated with Renewal (-0.301**), LogTotal (-0.209**), and both Z-scores of F1 (-0.087**) and F2 (-0.118**), mirroring the negative patterns seen in Table 1 and implying that longer durations may deter renewal and reduce engagement metrics. A notable exception is Reader Type, which has a non-significant correlation with Z-score F2 (0.008, p = 0.052) in this larger sample, suggesting no meaningful association.

Cross-table comparisons reveal key insights: the strong positive correlation between Renewal and LogTotal (≈0.38) is consistent across both samples, underscoring its robustness, while the negative association between Time and engagement metrics (Renewal, LogTotal) holds in both datasets, indicating time may act as a deterrent to renewal and higher total values. Regarding factor scores, Z-score F1 has a stronger correlation with LogTotal in Table 1 (0.427**) than in Table 2 (0.378**), whereas Z-score F2 shows a stronger link with LogTotal in Table 2 (0.511**), reflecting sample-specific variance in factor contributions. For Reader Type, the larger sample in Table 2 yields weaker correlations with most variables compared to Table 1, except for a marginally significant association with Z-score F1 (0.117**), while the non-significant correlation with Z-score F2 (0.008) highlights how sample size influences statistical significance.

Table 2. Correlations for females (N = 60,670).

Variables	Reader type	Renewal	Time	LogTotal	Z-score F1	Z-score F2
Reader type	1	0.081**	0.099**	0.049**	0.117**	0.008
Renewal	0.081**	1	0.382**	-0.301**	0.210**	0.246**
LogTotal	0.099**	0.382**	1	-0.209**	0.378**	0.511**
Time	0.049**	-0.301**	-0.209**	1	-0.087**	-0.118**
Z-score F1	0.117**	0.210**	0.378**	-0.087**	1	0.000
Z-score F2	0.008	0.246**	0.511**	-0.118**	0.000	1

Note: "**" indicates that the correlation coefficient is significant at the 0.01 level (Two-tailed test).

The analysis highlights several critical insights. First, Renewal and LogTotal emerge as key drivers, demonstrating a strong interdependence and positive association with both factor scores (F1 and F2). This suggests they likely reflect shared underlying user engagement patterns, such as consistent interaction or participation metrics. Second, Time acts as a notable negative factor: longer durations are consistently linked to lower renewal rates and reduced engagement, indicating a need for further investigation into how user behavior evolves, for example, whether extended periods correlate with diminishing interest or changing needs. Sample variability also plays a significant role: smaller samples (e.g., Table 1) may overstate weak correlations, such as the association between Reader Type and Z-score F2 (0.101**), whereas larger samples (e.g., Table 2) provide more precise estimates, reducing the likelihood of false positives and emphasizing the importance of sample size in interpreting correlation strength. While all significant correlations ($p < 0.01$) indicate statistically meaningful relationships, their practical significance must be evaluated alongside effect sizes and contextual factors, such as the specific user population or operational context, to avoid overinterpreting minor associations. Overall, the findings underscore the value of considering statistical rigor and real-world relevance when analyzing interdependencies among user engagement metrics.

4.5. Book Renewal

4.5.1. Binary Logistic Regression Analysis of Book Renewal for Male Readers

The analysis examines the predictors of book renewal behavior among male readers (N = 19,873) using binary logistic regression. This analysis, conducted using SPSS's MATRIX procedure, employs a logistic regression model for the binary outcome variable Renewal to examine the interaction between the core predictor LogTotal and the moderator Time, while including Z-score F1, Z-score F2, Z-score F3, and Reader as covariates. With a sample size of 19,873, the model demonstrates a significant overall fit (-2LL = 12,580.970, ModelLL = 4,681.430, $p < 0.001$), explaining 27.12% of the variance in renewal decisions (McFadden pseudo-R^2 = 0.271), indicating a moderate fit. For core variables, LogTotal has a significant main effect (coefficient = 3.107, $p < 0.001$), meaning higher log-transformed total amounts are associated with greater log-odds of renewal. The main effect of Time is non-significant (coefficient = -0.034, p = 0.648), but the interaction term Int_1 (LogTotal × Time) is highly significant (coefficient = -0.847, $p < 0.001$), suggesting that the positive effect of LogTotal on renewal weakens over time.

Among covariates, Z-score F3 (coefficient = 0.130, $p < 0.001$) and Reader (coefficient = 0.628, $p < 0.001$) have significant positive effects on renewal, with the former increasing log-odds by 0.130 per unit and the latter indicating significantly higher renewal log-odds for readers. Z-score F1 has no significant effect (p = 0.647), while Z-score F2 shows marginal significance (p = 0.079). Overall, the model reveals a dynamic interaction between LogTotal and Time, highlighting that the predictive power of total amount for renewal is strongest in the early stages. Reader status and the specific factor Z-score F3 emerge as consistent drivers of renewal across different time points.

Table 3. The estimated effect of LogTotal on renewal at three periods.

Time (W)	Effect of LogTotal (Coeff.)	S.E.	Z-score	p-value	95% CI
2016-2018	2.260	0.066	34.030	<0.001	2.130 to 2.390
2019-2021	1.413	0.059	24.110	<0.001	1.298 to 1.528
2022-2024	0.566	0.097	5.860	<0.001	0.377 to 0.755

Table 3 shows the estimated effect of LogTotal on renewal across three periods: 2016–2018, 2019–2021, and 2022–2024, based on a logistic regression model with a significant interaction between LogTotal and Time. The results reveal a clear temporal decline in LogTotal's impact on renewal: in the earliest period (2016–2018), a one-unit increase in LogTotal was associated with a 2.260 log-odds increase in renewal ($p < 0.001$), indicating a strong positive effect. By the middle period (2019–2021), this effect dropped to 1.413 log-odds ($p < 0.001$), a reduction of approximately 37.5%, and further fell to 0.566 log-odds ($p < 0.001$) in the latest period (2022–2024), less than a quarter of the initial effect. Despite the decreasing magnitude, all estimates remain highly statistically significant, suggesting LogTotal remains a relevant but weaker predictor over time. This pattern aligns with the model's interaction term, where the negative coefficient for LogTotal × Time (-0.847) confirms the diminishing effect of LogTotal as time progresses. Practically, the findings imply that leveraging high LogTotal values to drive renewal is most effective in the early stages (2016–2018), while other factors likely dominate renewal decisions in later periods (2019–2024).

4.5.2. Binary Logistic Regression Analysis of Book Renewal for Female Readers

Using binary logistic regression, the analysis examines predictors of book renewal behavior among female readers (N = 60,670). This analysis, utilizing SPSS's MATRIX procedure, employs a logistic regression model to examine the binary outcome Renewal, with LogTotal (log-transformed total amount) as the core predictor and Time as the moderator, while including Z-score F1, Z-score F2, and Reader as covariates. With a sample size of 60,670, the model demonstrates a significant overall fit (-2LL = 40,810.470, ModelLL = 14,519.760, $p < 0.001$), explaining 26.24% of the variance in renewal decisions (McFadden pseudo-R^2 = 0.2624), indicating a moderate but meaningful fit.

For core variables, LogTotal exhibits a strong positive main effect (coefficient = 3.295, $p < 0.001$), meaning higher log-transformed total amounts are significantly associated with greater log-odds of renewal. The main effect of Time is non-significant (coefficient = -0.003, $p = 0.9517$), but the interaction term Int_1 (LogTotal × Time) is highly significant (coefficient = -0.974, $p < 0.001$), revealing that the positive impact of LogTotal on renewal diminishes over time.

Among covariates, Z-score F1 (coefficient = 0.048, $p < 0.001$) and Reader (coefficient = 0.432, $p < 0.001$) have significant positive effects on renewal, with the former increasing renewal log-odds by 0.0477 per unit and the latter indicating that reader status significantly boosts renewal likelihood. Z-score F2 has no statistically significant effect ($p = 0.921$). Overall, the model highlights a dynamic interaction between LogTotal and Time, underscoring that the predictive power of total amount for renewal is most pronounced in the early stages. Reader status and Z-score F1 emerge as consistent drivers of renewal across different time frames, providing a data-driven foundation for stage-specific renewal strategies.

Table 4. The estimated effect of LogTotal on renewal at three periods.

Time (W)	Effect of LogTotal (Coeff.)	S.E.	Z-score	p-value	95% CI
2016-2018	2.321	0.042	55.760	<0.001	2.240 to 2.403
2019-2021	1.348	0.037	36.320	<0.001	1.275 to 1.420
2022-2024	0.374	0.061	6.130	<0.001	0.255 to 0.494

Table 4 presents the estimated effects of LogTotal on renewal across three periods (2016–2018, 2019–2021, 2022–2024) from a logistic regression model with a significant LogTotal × Time interaction. The results reveal a striking temporal decline in LogTotal's impact: in the earliest period (2016–2018), a one-unit increase in LogTotal was associated with a 2.321 log-odds increase in renewal ($p < 0.001$), indicating a strong positive effect. By the middle period (2019–2021), this effect diminished to 1.348 log-odds ($p < 0.001$), a 41.1% reduction, and further declined to 0.374 log-odds ($p < 0.001$) in the latest period (2022–2024), an 83.9% reduction from the initial effect. Despite these decreases, all estimates remained highly significant, with narrow confidence intervals excluding zero, confirming LogTotal's persistent but weakening predictive power. Standard errors increased slightly over time (from 0.042 to 0.061), reflecting marginally lower precision in later periods, while z-scores declined from 55.76 to 6.13, mirroring the diminishing effect size. These findings align with the model's interaction term, which quantifies the attenuation of LogTotal's impact over time. Practically, the results suggest that strategies prioritizing high LogTotal values (e.g., targeting high-spending clients) are most effective during the early lifecycle stages (2016–2018), while later periods (2019–2024) require alternative retention drivers, such as service quality or engagement.

4.6. Two-Stage Least Squares Analysis

4.6.1. Regression Coefficients for Males' LogTotal as the Dependent Variable

This linear regression model uses LogTotal as the dependent variable and includes three independent variables: Z-score F1, Z-score F2, and Time, constructed using the Enter method. The overall model fit shows a correlation coefficient (R) of 0.563, indicating a moderate association between the predictors and the dependent variable. The coefficient of determination (R Square) is 0.317, meaning the model explains approximately 31.7% of the variation in LogTotal. The Adjusted R Square (0.317) is nearly identical to R Square, suggesting minimal bias from the number of predictors. The standard error of the estimate is 0.507, reflecting the average prediction error around the regression line. The ANOVA results show a regression sum of squares of 2364.349 and a mean square of 788.116, with an extremely high F-value of 3068.440 and a significance level (Sig.) below 0.001. This indicates that the three independent variables collectively have a statistically significant predictive effect on LogTotal.

As depicted in Table 5, the coefficients for the regression model reveal the individual impact of each predictor on the dependent variable LogTotal. The constant term (1.009) is highly significant (t = 113.451, p < 0.001), representing the expected value of LogTotal when all predictors are zero. Among the predictors, Time exhibits a significant negative effect, with an unstandardized coefficient of -0.062 (t = -13.999, p < 0.001), indicating that a one-unit increase in Time is associated with a 0.062 decrease in LogTotal, holding other variables constant. The standardized coefficient (Beta = -0.081) suggests this effect is relatively weak compared to other predictors. The z-scored factor variables show strong positive associations. Z-score F1 has the largest impact, with an unstandardized coefficient of 0.260 (t = 73.021, p < 0.001) and a standardized coefficient (Beta = 0.424), meaning a one standard deviation increase in F1 corresponds to a 0.260 increase in LogTotal—the strongest relative effect in the model. Z-score F2 follows closely (B = 0.215, Beta = 0.350, t = 60.305, p < 0.001), while Z-score F3 has a smaller but still significant effect (B = 0.078, Beta = 0.128, t = 21.992, p < 0.001). All predictors are highly statistically significant (p < 0.001), with their standardized coefficients ranking F1 > F2 > F3 > Time in terms of influence. The results suggest that F1 and F2 are the primary drivers of variation in LogTotal, while Time has a more modest negative association. The consistency of significant t-values across predictors underscores the model's reliability in estimating these relationships.

Table 5. Coefficients of linear regression for males[a].

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	1.009	0.009	--	113.451	0.000
	Time	**-0.062**	0.004	-0.081	-13.999	0.000
	Z-score F1	**0.260**	0.004	0.424	73.021	0.000
	Z-score F2	**0.215**	0.004	0.350	60.305	0.000
	Z-score F3	**0.078**	0.004	0.128	21.992	0.000

Note: a. Dependent variable: LogTotal.

Next Step: Two-Stage Least Squares (2SLS) Analysis.

To address potential endogeneity or measurement error, save the standardized predicted variables from this linear regression and use them as instruments in a Two-stage Least Squares Analysis. This will help estimate causal effects more accurately by isolating the exogenous variation in the predictors.

The two-stage least squares (2SLS) analysis presents a regression model where the dependent variable is likely related to LogTotal (inferred from prior context), with predictors including Renewal, Reader, and ZPR_1. The model demonstrates a moderate fit, explaining 37.9% of the variance in the dependent variable ($R^2 = 0.379$), with a slightly higher multiple correlation coefficient (R = 0.616) indicating a stronger linear association between predictors and the outcome. The ANOVA result is highly significant (F = 4,039.670, p < 0.001), confirming that the combined predictors meaningfully influence the dependent variable.

In the coefficients Table 6, all predictors exhibit statistically significant effects (p < 0.001). The constant term (0.749) is significant (t = 79.134), representing the baseline value of the dependent variable when all predictors are zero. Renewal has a positive unstandardized coefficient (0.356) and a standardized coefficient (Beta = 0.211), indicating that a one-unit increase in Renewal is associated with a 0.356 increase in the dependent variable, with a moderate relative impact. Reader type shows a smaller but significant effect (B = 0.056, Beta = 0.057), suggesting a weaker positive association. ZPR_1 is the strongest predictor, with an unstandardized coefficient of 0.308 and a Beta of 0.502, the highest among the variables, indicating that a one standard deviation increase in ZPR_1 corresponds to a 0.308 increase in the dependent variable, explaining half of the standardized variance. The large t-values (e.g., 84.842 for ZPR_1) reflect high precision in estimating these coefficients, likely due to the large sample size (n = 19,872).

As a predictor variable, ZPR_1 exhibits regression coefficients (B=0.308, Beta=0.502) that are significantly higher than those of Time (B=-0.025, Beta=-0.032), Z-score F1 (B=0.232, Beta=0.379), Z-score F2 (B=0.187, Beta=0.305), and Z-score F3 (B=0.065, Beta=0.105) (see Table 7). Additionally, its t-value

(81.992) is the largest among these variables, indicating a stronger and more independent direct effect on the dependent variable.

Table 6. Coefficients of 2SLS for males (I).

Model		Unstandardized coefficients		Beta	t	Sig.
		B	Std. error			
Equation 1	(Constant)	0.749	0.009	--	79.134	0.000
	Renewal	0.356	0.010	0.211	35.452	0.000
	Reader type	0.056	0.006	0.057	10.106	0.000
	ZPR_1	**0.308**	0.004	0.502	84.842	0.000

Table 7. Coefficients of 2SLS for males (II).

Model		Unstandardized coefficients		Beta	t	Sig.
		B	Std. error			
Equation 1	(Constant)	0.797	0.012	--	64.581	0.000
	Renewal	0.371	0.010	0.220	36.157	0.000
	Reader type	0.053	0.006	0.054	9.552	0.000
	Time	-0.025	0.004	-0.032	-5.599	0.000
	Z-score F1	0.232	0.003	0.379	66.371	0.000
	Z-score F2	0.187	0.004	0.305	53.331	0.000
	Z-score F3	0.065	0.003	0.105	18.722	0.000

4.6.2. Regression Coefficients for Females' LogTotal as the Dependent Variable

This linear regression model employs LogTotal as the dependent variable, incorporating three independent variables: Z-score F1, Z-score F2, and Time, using the Enter method. The model demonstrates a moderate-to-strong fit, with an R value of 0.646, indicating a substantial linear association between the predictors and the dependent variable. The R Square of 0.417 suggests that the model explains approximately 41.7% of the variance in LogTotal, and the Adjusted R Square of 0.417 confirms no significant bias from the number of predictors, reinforcing the model's reliability. The standard error of the estimate is 0.440, reflecting a relatively low average prediction error. The ANOVA results show a highly significant model, with an F-value of 14,480.465 ($p < 0.001$). The regression sum of squares (8,400.123) and mean square (2,800.041) highlight the collective explanatory power of the predictors. All independent variables exhibit statistically significant effects:

As depicted in Table 8, Time has a significant negative impact, with an unstandardized coefficient of -0.085 ($t = -37.852$, $p < 0.001$), indicating that a one-unit increase in Time is associated with a 0.085-unit decrease in LogTotal. Z-score F1 ($\beta = 0.368$, $t = 118.178$, $p < 0.001$) and Z-score F2 ($\beta = 0.497$, $t = 159.085$, $p < 0.001$) have strong positive effects, with Z-score F2 being the most influential predictor. Their standardized coefficients suggest that Factor 3 explains nearly half of the variance in LogTotal, making it the core driver in the model. The covariance between Z-score F1 and Z-score F2 is 7.827 ($p < 0.001$), with a moderately strong correlation ($r = 0.590$). This indicates a significant but not extreme association, supporting their distinctiveness as related yet separate constructs.

Table 8. Coefficients of linear regression for females.

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	Beta		
1	(Constant)	1.096	0.005	--	242.822	0.000
	Time	**-0.085**	0.002	-0.119	-37.852	0.000
	Z-score F1	**0.212**	0.002	0.368	118.178	0.000
	Z-score F2	**0.286**	0.002	0.497	159.085	0.000

Note: a. Dependent variable: Log total.

The 2SLS model outperforms the original linear regression in both goodness-of-fit and explanatory power. With a Multiple R of 0.667 and an R Square of 0.444 (up from 0.317 in the original model), the 2SLS model explains a larger proportion of the variance in LogTotal. The Adjusted R Square (0.444) aligns with R Square, and the Standard Error of the Estimate decreases from 0.507 to 0.429, indicating improved prediction accuracy. The ANOVA results show an F-value of 16,176.087 ($p < 0.001$), confirming the model's statistical significance.

In the coefficients Table 9, ZPR_1 exhibits regression coefficients (B=0.336, Beta=0.583) that are significantly higher than those of Time (B=-0.055, Beta=-0.077), Z-score F1 (B=0.190, Beta=0.330), and Z-score F2 (B=0.264, Beta=0.459) (see Table 10). Additionally, its t-value (179.231) is the largest among these variables, indicating a stronger and more independent direct effect on the dependent variable.

Table 9. Coefficients of 2SLS for females (I).

Model		Unstandardized coefficients		Beta	t	Sig.
		B	Std. error			
Equation 1	(Constant)	0.822	0.005	--	163.368	0.000
	Renewal	0.255	0.005	0.166	51.015	0.000
	Reader type	0.050	0.003	0.048	15.832	0.000
	ZPR_1	**0.336**	0.002	0.583	179.231	0.000

Table 10. Coefficients of 2SLS for females (II).

Model		Unstandardized coefficients		Beta	t	Sig.
		B	Std. error			
Equation 1	(Constant)	0.924	0.006	--	142.434	0.000
	Renewal	0.265	0.005	0.173	51.989	0.000
	Reader type	0.048	0.003	0.046	15.095	0.000
	Time	**-0.055**	0.002	-0.077	-24.045	0.000
	Z-score F1	**0.190**	0.002	0.330	105.800	0.000
	Z-score F2	**0.264**	0.002	0.459	146.634	0.000

5. Discussion

This study reveals multidimensional gender differences in reading behaviors through analyses of book borrowing distributions, reading preferences, factor structures, correlations, and renewal patterns among male and female readers, providing empirical evidence for understanding reader behavior models. The following discussion expands on core findings, theoretical and practical implications, interdisciplinary perspectives, and refined directions for future research.

5.1. Underlying Drivers of Borrowing Distribution Differences: Interplay of Social Roles and Reading Purposes

The broad distribution and extreme values in female borrowing volumes may stem from diversified reading needs arising from multiple social roles (e.g., working women, mothers, researchers). For example, heavy borrowers might simultaneously engage in academic research and family education, requiring cross-disciplinary information (e.g., parenting guides, professional literature), leading to bimodal borrowing patterns. In contrast, the centralized borrowing volumes among males may relate to the goal-oriented reading model shaped by traditional gender roles—topics like military and transportation often directly align with professional skill development (e.g., engineers, military enthusiasts), making reading more planned and avoiding resource redundancy. This difference confirms the gender socialization theory, where societal expectations mold information-seeking strategies by gender (Hossain, 2024; Shapiro, 2019; Tomar et al., 2024). Women's reading behaviors here reflect the emotional labor theory, as they often use reading for emotional management and interpersonal understanding, which is rooted in their socially constructed roles (Andermann, 2010; Crawford & Roger, 2012; Thums et al., 2021).

5.2. Cultural Construction of Reading Preferences: Perpetuation and Subversion of Gender Stereotypes

Women's dominance in humanities and social sciences may reflect both gender socialization (e.g., early encouragement of literature and art) and the emotional labor theory—women often use reading for emotional management and interpersonal understanding (Hossain, 2024; Thums et al., 2021). Men's preferences for STEM fields, beyond traditional gender roles, may relate to the cognitive need theory: the logical and problem-solving nature of technical content aligns with males' preference for challenging cognitive tasks (Crawford & Roger, 2012). Notably, while women's borrowing in applied sciences (e.g., medicine, agriculture) is lower than males', it exceeds military/transportation categories, suggesting gender differences are not absolute and some scientific subfields (e.g., biomedicine, horticulture) may be more female-friendly (Casals, 2023). This aligns with the understanding that gender roles are sociocultural constructs rather than biological determinants (Shapiro, 2019).

5.3. Gender Differences in Factor Structures: Cognitive Patterns and Interest Integration

The low correlation among factors in the male three-factor model implies that modular reading interests (F2, F1, F3 domains) are relatively independent, reflecting a domain-specific cognitive tendency (Reilly et al., 2022). For instance, military enthusiasts (F3) may rarely engage with literature (F1), focusing instead on deep specialization. The strong correlation in the female two-factor model (r=0.590) indicates intersecting interests, such as synergistic reading of literature (F1) and art (F2), consistent with a holistic cognitive pattern that builds knowledge networks across disciplines. This difference may relate to brain lateralization hypotheses—stronger interhemispheric connectivity in females supports multitasking and conceptual integration (Holmshaw & Hillier, 2000). Socially, women's need to balance multiple roles (e.g., work and family) may also foster this integrative cognitive style (Jiao et al., 2021; Wong & Waldner, 2021).

5.4. Temporal Dynamics of Renewal Behavior: Lifecycle Stages vs. Reading Inertia

The slower decay of the LogTotal effect in male renewal (37.5% reduction) compared to females (83.9%) may reflect gender differences in reading habits: once males establish a reading pattern (e.g., regular technical journal borrowing), they are more likely to maintain it long-term, possibly due to stable professional roles (Agranovich et al., 2021; Vokic & Mrdenovic, 2008). Females, however, are more affected by life stage changes (e.g., childbirth, career transitions), causing fluctuating needs (Hu, Yan, Wen, & Wang, 2024; Jabbar & Warraich, 2023). For example, the minimal LogTotal effect among females in 2022–2024 (0.37) may relate to post-pandemic remote work and parenting pressures fragmenting reading time, which aligns with the impact of sociocultural factors on women's health and well-being (Alexander & Walker, 2015; Ostrowska, 2012). Additionally, the diminishing marginal utility theory explains the universal decline in renewal willingness: as borrowing increases, satisfaction with existing resources decreases, necessitating new content to stimulate renewals.

5.5. Cross-Gender Commonality: Time as a Hidden Barrier to Reading Behavior

Despite gender differences in renewal patterns, the universal negative impact of time on renewal and borrowing volume (Tables 3–4, 7–8) may reflect the objective forgetting curve—longer intervals reduce demand for borrowed resources. It may also relate to library service reach, such as reduced personalized recommendations for inactive users (Adetayo, 2024; Applegate, 2008; Dixon et al., 2014). Practically, a reading lifecycle management strategy could be adopted: intensifying engagement with active users (2016–2018) and promoting cross-disciplinary themes to reactivate dormant users (2022–2024). Gender differences in time management (Aeon et al., 2021; Codina & Pestana, 2019) suggest tailored approaches, such as lightweight reading recommendations for women's fragmented time and thematic deep-reading paths for men.

5.6. Theoretical Expansion: Toward an Integrated Model of Gender and Reading Behavior

Findings can be integrated into the social cognitive theory framework, emphasizing dynamic interactions between gender self-concept (e.g., I am a technology enthusiast), environmental stimuli (e.g., library thematic displays), and behavioral outcomes (e.g., renewal) (Bandura, 1986). For example, males' preference for military topics may reflect both self-identity and environmental cues (e.g., military-themed exhibitions, male librarian recommendations) (Shapiro, 2019; Tomar et al., 2024). Future research could use SEM with mediation analysis to test the causal chain: gender identity → preference category → borrowing volume → renewal, quantifying the weight of each link (Bolte, Nanninga, & Dandolo, 2019; Kenzheali, Kenzhegulova, Kireyeva, & Ainakul, 2024).

6. Conclusion

This study analyzes the book borrowing behaviors of users at Nanjing Normal University Library across the pre-pandemic (2016—2018), pandemic-impact (2019—2021), and post-pandemic recovery (2022—2024) periods. Data from the library's information system, including borrowing timestamps, user demographics, book categories, and renewal status, were cleaned and categorized by gender, user type, borrowing volume, and periods. PCA identified latent factors in borrowing patterns, with males showing three distinct factors and females two, though some variables exhibited weak loadings in structural equation models. Binary logistic regression revealed that the positive effect of log-transformed total borrowing volume on renewal behavior diminished over time for both genders, with faculty/staff more likely to renew, and specific factor scores (e.g., F3 for males, F1 for females) influencing outcomes. Two-stage Least Squares (2SLS) models demonstrated that standardized predicted values integrating multiple factors explained borrowing volume better than individual factors, highlighting their comprehensive explanatory power. Gender differences were evident: females borrowed more variably, favoring humanities/social science categories, while males preferred military, transportation, and STEM fields. The pandemic period marked a decline in borrowing and renewal, with time negatively correlated with engagement metrics. Limitations include the single-institution focus, potential unobserved variables, aggregated book categories, and factor stability issues. Future research could expand to multi-institutional data, employ machine learning, explore causal mechanisms via experimental designs, and delve into qualitative insights on gender and disciplinary preferences to enhance library strategies and user engagement.

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