Four Easy Payments, One Difficult Question

Do Behavioural Biases Exhibit Stronger Positive Associations with Buy Now, Pay Later Usage than Financial Necessity?

NDH900 Degree Project in Retail Management

BSc Retail Management Programme

Stockholm School of Economics

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Abstract

Buy Now, Pay Later (BNPL) has rapidly emerged as a widely adopted payment solution within retail and fintech. While prior research associates BNPL usage with both financial necessity and behavioural biases, these factors have largely been examined separately. This study addresses this gap by comparing the relative influence of financial and behavioural factors on BNPL usage frequency within a single integrated framework. Using a quantitative cross-sectional survey design, data from 166 respondents were analysed through descriptive statistics and regression analysis. The findings indicate that certain behavioural variables, particularly mental accounting and instalment preference, exhibit more consistent positive associations with BNPL usage frequency than financial necessity. The study contributes to the BNPL literature by integrating behavioural and financial perspectives and provides implications for retailers, fintech firms, and policymakers regarding consumer decision-making and responsible payment design.

Keywords: Buy Now, Pay Later (BNPL), consumer credit, financial constraint, behavioural biases, mental accounting, pain of payment, instalments, electronic payments, behavioural economics.

Acknowledgements

We would like to express our sincere gratitude to everyone who supported us throughout the process of writing this thesis. First, we would like to thank our supervisor, Carin Rehncrona, for her continuous guidance, support, and valuable feedback throughout the entire process.

We would also like to extend our sincere thanks to Sara Rosengren for her valuable advice and for conducting insightful seminars on how to approach and complete the thesis in the best possible way.

Finally, we would like to acknowledge the Stockholm School of Economics for providing us with valuable knowledge and insights through many courses during our studies. The knowledge and experiences gained throughout the programme have been essential in the completion of this thesis.

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1. Introduction

1.1 Context

Buy Now, Pay Later (BNPL) has rapidly emerged as a significant payment method within retail and fintech. BNPL is a short-term, typically interest-free credit financing solution that allows consumers to defer payment by splitting up the purchase cost into an initial payment followed by a number of equal instalments, usually three or four, over a set period (Jose et al. 2025; Guttman-Kenney et al. 2023; Aidala et al. 2025; Ashby et al. 2025; Consumer Financial Protection Bureau 2025). Due to its seamless integration into e-commerce platforms and partnerships with fintech providers such as Klarna and Afterpay, BNPL has become increasingly prevalent in online retail environments (Jose et al. 2025; Guttman-Kenney et al. 2023; Svahn 2023; Cornelli et al. 2023; Kumar et al. 2024).

The growing importance of BNPL is reflected in both consumer adoption and academic interest. Globally, BNPL activity increased sixfold between 2019 and 2023 (Cornelli et al. 2023). It has also been shown that nearly 25% of e-commerce transactions in Sweden were financed through BNPL in 2022 (Svahn 2023). Simultaneously, research on BNPL is expanding considerably, highlighting its increasing economic and societal relevance.

Existing literature suggests that BNPL usage is associated with both financial and behavioural factors. Prior studies consistently identify financial constraints as a factor positively associated with the use of BNPL services (Consumer Financial Protection Bureau 2025; Chen et al. 2024; Di Maggio et al. 2022; Aidala et al. 2025; Guttman-Kenney et al. 2023; Cornelli et al. 2023). At the same time, the use of BNPL methods cannot be attributed to financial constraints alone, but should also be understood through psychological mechanisms, including cognitive biases that influence consumer behaviour (Di Maggio et al. 2022; Jose et al. 2025; Relja et al. 2023). While we recognise that additional factors, such as consumer security aspects and convenience in online shopping environments (Svahn 2023), may also contribute to BNPL usage, this study focuses specifically on financial constraints and cognitive biases as the primary explanatory factors underlying BNPL usage.

1.2 Research gap

As previously discussed, prior research suggests that both financial necessity and behavioural biases are associated with BNPL usage. However, these factors have largely been examined separately, leaving it unclear which exhibits stronger associations with BNPL usage frequency. This study addresses this gap by comparing the relative importance of financial necessity and behavioural biases in relation to BNPL usage frequency.

1.3 Research purpose and questions

The purpose of this study is to examine the associations between behavioural biases, financial necessity, and BNPL usage frequency, and to compare the relative importance of financial and behavioural factors in explaining variations in BNPL usage frequency. Accordingly, the study addresses the following research questions:

RQ1: How is mental accounting associated with BNPL usage frequency?

RQ2: How is financial necessity associated with BNPL usage frequency?

RQ3: Do behavioural variables exhibit stronger associations with BNPL usage frequency than financial necessity?

1.4 Contribution

The primary theoretical contribution of this study lies in integrating two previously separate explanatory perspectives on BNPL usage: financial necessity and behavioural biases. By examining these factors within a unified framework, the study contributes to a more comprehensive understanding of the behavioural and financial dimensions associated with BNPL usage.

From a managerial perspective, the findings provide implications for fintech firms in the strategic design and positioning of BNPL services. The study further suggests that retailers should recognise that BNPL appeals not only to liquidity-constrained consumers, but also to financially unconstrained customers, potentially contributing to increased consumer spending and higher conversion rates. Finally, the findings indicate that policymakers should place equal emphasis on both behavioural and financial dimensions when regulating BNPL services.

1.5 Structure

The following study is structured as follows: Initially, a review of the literature on BNPL, financial constraints, and behavioural biases is presented, followed by the identification of the research gap and the development of hypotheses. Subsequently, the methodological framework and empirical analysis are outlined. The study concludes with a discussion of the findings, their theoretical and managerial implications, the study's limitations, and suggestions for future research.

2. Literature review

2.1 Buy Now, Pay Later (BNPL)

Buy Now, Pay Later (BNPL) is a short-term, typically interest-free credit financing solution that allows consumers to defer payment for their purchases into the future. After making a purchase, consumers using BNPL typically repay the purchase price in an upfront payment followed by a number of interest-free instalments over the course of a specified time period (Guttman-Kenney et al. 2023; Aidala et al. 2025; Ashby et al. 2025; Consumer Financial Protection Bureau 2025). By enabling immediate consumption and delayed payment, BNPL inherently decouples the moment of purchase from the moment of payment. For example, a consumer purchasing a 4000 SEK laptop through BNPL may receive the product immediately while only paying 1000 SEK upfront and spreading the remaining amount across future instalments. This temporal separation of purchase and payment, combined with BNPL's interest-free nature, has been suggested to alter the psychological experience of spending by reducing the perceived pain of paying and consequently influencing consumers' purchasing behaviour, perceptions of affordability, and credit usage patterns (Jose et al. 2025; Valenciano et al. 2025; Di Maggio et al. 2022; Relja et al. 2023).

In addition to its suggested influence on consumer behaviour, BNPL is commonly observed in online retail settings. Most commonly provided in collaboration with third-party fintech companies such as Klarna and Afterpay, e-commerce platforms have been at the forefront of seamlessly integrating BNPL into their online checkout process as an additional form of digital payment solution (Jose et al. 2025; Guttman-Kenney et al. 2023; Svahn 2023; Cornelli et al. 2023; Kumar et al. 2024).

Drawing on these characteristics, including deferred payment, interest-free instalments, and seamless online integration, BNPL serves as a highly convenient and low-friction payment method for consumers. Consequently, it is little surprising that several sources indicate BNPL's growing significance as a payment method: on a global scale, Cornelli et al. (2023) show that BNPL activity increased sixfold from 2019 to 2023. In 2023 in the U.S. 20% of consumers surveyed by the New York Federal Reserve reported having used BNPL in the past (Wang 2025; Aidala et al. 2024). In Sweden, where the share of BNPL payments in e-commerce is the highest in the world, nearly 25% of all e-commerce transactions were financed using BNPL based on market research data in 2022 (Svahn 2023).

Similarly, in academia, a rapidly growing pattern of research output focused on BNPL can be discovered. Using the Boolean search term "BNPL" OR "buy now pay later" on Scopus, a curated scientific database for peer-reviewed literature, our bibliometric analysis revealed that scholarly attention paid to BNPL has intensified markedly since the early 2020s. The number of publications increased from 6 in 2022 to 19 in 2023, representing more than a threefold increase, with output rising further to 46 publications in 2024, more than doubling compared to 2023. This upward trend appears to continue until today, with 59 documented publications in 2025 and 11 publications already recorded in January 2026 (*see Figure 1, Appendix*). Overall, the fact that BNPL-related research expanded from 6 publications in 2022 to 59 in 2025, corresponding to an almost tenfold increase (≈ + 883%) within just three years, provides additional evidence of the growing economic and societal relevance of BNPL.

Indeed, thanks to the continuously amplifying research focused on BNPL, many insightful observations have already accumulated, enriching the understanding of the phenomenon. Research into the socio-economic profile of BNPL users has generally concluded that BNPL usage appears to be concentrated among younger and financially constrained groups (Aidala et al. 2025; Cornelli et al. 2023; Healy et al. 2025; Di Maggio et al. 2022; Consumer Financial Protection Bureau 2025; Chen et al. 2024). Consistent with this finding, it has been observed that BNPL users typically have subprime credit scores and higher levels of indebtedness compared with non-users (Consumer Financial Protection Bureau 2025; Aidala et al. 2025; Guttman-Kenney et al. 2023; Cornelli et al. 2023). Collectively, these findings have suggested that liquidity constraints and financial stress are positively associated with BNPL usage.

However, as Di Maggio et al. (2022) highlight, BNPL usage cannot be explained by financial necessity alone, since even consumers with access to regular credit and positive savings buffers have been shown to make use of the payment method. Consequently, a growing body of research has focused on investigating other potential factors that could play a role in making consumers choose BNPL. Specifically, psychological factors such as behavioural biases have been examined as potential determinants of BNPL usage. Present bias, closely associated with the notion of hyperbolic discounting, refers to the human tendency to favour immediate rewards over later ones and avoid immediate costs. Prior research has associated this tendency with borrowing behaviour (Meier & Sprenger 2010; Kuchler & Pagel 2018; Bradford et al. 2018), including BNPL usage (Kumar et al. 2024; Waliszewski et al. 2024; Marisa et al. 2025).

Another concept that has been suggested to influence BNPL use among consumers is mental accounting. The concept originates from Richard Thaler's work (1985, 2008), and it refers to the cognitive process by which individuals categorise, evaluate, and track financial activities in separate mental "accounts," rather than treating money as fully fungible. In the context of BNPL, this mental compartmentalisation may lead consumers to evaluate instalment payments separately from total purchase costs, potentially increasing perceived affordability and spending propensity (Kumar et al. 2024; Jose et al. 2025; Di Maggio et al. 2022; Waliszewski et al. 2024).

Closely related to mental accounting is the concept of payment salience, also referred to as pain of paying (Prelec & Loewenstein 1998) or payment transparency, which refers to the extent to which consumers are psychologically aware of monetary outflows during a transaction. Prior research suggests that lower payment salience, particularly in electronic and credit-based payment contexts where payments are less tangible than cash transactions, may reduce consumers' psychological resistance to spending and increase perceived affordability (Relja et al. 2023; Soman 2003; Broekhoff & van der Cruijsen 2024). Consequently, BNPL has been suggested to reduce the perceived pain of paying and influence consumers' spending behaviour (Jose et al. 2025; Kumar et al. 2024; Guttman-Kenney et al. 2023; Kumar & Nayak 2025).

Taken together, BNPL has been documented as a growing credit payment solution among consumers. Its innovative and relatively novel nature however, including interest-free instalments, deferred payment, and wide accessibility through seamless online integration, clearly distinguishes BNPL from traditional credit financing instruments and has therefore impelled both academics and practitioners to start fresh research on BNPL's key characteristics, such as its antecedents and impact on consumers. The following sections review the literature on two of the most researched potential drivers of BNPL usage, namely financial necessity and behavioural biases, in greater detail, laying the foundation for this paper's contribution on examining how these two factors are simultaneously associated with BNPL use.

2.2 Financial constraint and BNPL

As discussed earlier, financial constraint has been commonly suggested to be positively associated with the usage of BNPL services (Consumer Financial Protection Bureau 2025; Chen et al. 2024; Di Maggio et al. 2022; Aidala et al. 2025; Guttman-Kenney et al. 2023; Cornelli et al. 2023). Conceptually, financial constraint refers to circumstances in which an individual has economic limitations that restrict desired consumption (Hamilton et al. 2018). Furthermore, findings suggest that this financial condition is associated with insufficient emergency savings, which constrains individuals' ability to absorb financial shocks and maintain stable consumption over time (Despard et al. 2020). Consequently, financially constrained individuals must adjust their consumption patterns in accordance with the economic limitations they face (Hamilton et al. 2018). Accordingly, financial constraints have been consistently associated with the use of BNPL services, as deferred, instalment-based payment options such as BNPL can alleviate short-term liquidity pressures and relax immediate budget constraints (Donou-Adonsou & Leslie-Piper 2025; Ji et al. 2023; Aidala et al. 2024). Empirical evidence further suggests that higher levels of financial constraint are not only linked to an increased likelihood of BNPL adoption, but also to greater usage frequency among those who adopt these services (Aidala et al. 2024).

In addition, a closely related economic state to financial constraint, financial fragility, should be considered. The concept of financially fragile individuals refers to someone who experiences financial insecurity and lacks sufficient emergency savings to cope with unexpected expenses. Prior research suggests that financially fragile individuals are significantly more likely to adopt BNPL services. Consequently, they not only exhibit a higher propensity to use such services but also tend to rely on them more frequently than financially stable consumers (Donou-Adonsou & Leslie-Piper 2025). Collectively, this pattern indicates that BNPL is commonly utilised by liquidity-constrained households, suggesting that its adoption may not solely be driven by convenience-based motivators, but may instead reflect more structural financial needs (Donou-Adonsou & Leslie-Piper 2025).

A number of underlying mechanisms have been identified to explain the suggested relationship between financial constraint and BNPL usage. Initially, a clear and readily identifiable explanation is that BNPL serves as a mechanism for consumption smoothing among liquidity-constrained individuals (Guttman-Kenney et al. 2023; deHaan et al. 2024). By postponing immediate payment obligations, BNPL enables consumers to proceed with purchases despite lacking sufficient available funds, and at the same time avoid bank overdrafts (deHaan et al. 2024). Accordingly, BNPL serves as a short-term liquidity solution for consumers who anticipate future income but currently face a temporary cash-flow gap (Ji et al. 2023), which facilitates consumption that might otherwise have to be postponed or forgone entirely due to insufficient immediate liquidity. Similarly, the condition of financial fragility may lead individuals to rely on BNPL when they lack the liquidity required to absorb unexpected expenditures through savings (Donou-Adonsou & Leslie-Piper 2025) and therefore turn to short-term payment alternatives to bridge the gap.

2.3 Behavioural biases and BNPL

The use of BNPL methods cannot be attributed exclusively to financial necessity, but should also be examined considering psychological mechanisms, including various cognitive biases that influence consumer behaviour (Di Maggio et al. 2022; Jose et al. 2025; Relja et al. 2023). To begin with, the concept of present bias has been suggested as one of several factors associated with BNPL usage (Kumar et al. 2024; Waliszewski et al. 2024; Marisa et al. 2025). Present bias, often termed “hyperbolic discounting”, is defined as the tendency to favour a smaller immediate reward over a larger delayed one, but reversing this preference when both rewards are delayed by the same amount of time (Chakraborty 2021; Kumar et al. 2024). A clear illustrative example is that a customer with present bias is more likely to choose $100 immediately rather than $110 in four weeks. However, they are less likely to prefer the smaller, sooner reward when the choice is between $100 in 26 weeks and $110 in 30 weeks, even though the time gap between the two options remains four weeks. In this case, both rewards are simply delayed by the same amount of time, yet the preference changes (Coller & Williams 1999). This psychological behaviour among consumers has been shown to result in undesirable spending and borrowing patterns (Xiao &

Porto 2019), demonstrating that time-inconsistent preferences can actually encourage borrowing behaviour (Meier & Sprenger 2010; Kuchler & Pagel 2018; Bradford et al. 2018). More specifically, present bias has been suggested to increase the attractiveness of BNPL services as payment options because they allow consumers to obtain immediate consumption while postponing the financial sacrifice associated with the payment (Kumar et al. 2024; Waliszewski et al. 2024; Marisa et al. 2025).

In addition to present bias, the concept of mental accounting has also been suggested to be associated with BNPL services (Kumar et al. 2024; Jose et al. 2025; Di Maggio et al. 2022; Waliszewski et al. 2024). Based on Thaler's work (1985, 2008), mental accounting can be defined as the cognitive process through which individuals mentally organise, categorise, evaluate, and track financial outcomes and transactions in separate mental accounts, rather than treating money as fully fungible, thereby shaping economic decision-making and consumer behaviour. One example of such a mental accounting process is narrow bracketing, where consumers evaluate individual payments or instalments in isolation rather than considering the total cumulative cost of a purchase (Thaler 1999; Koch & Nafziger 2016). In the context of BNPL, such mental compartmentalisation may lead consumers to treat future instalment obligations as separate from current income or total purchase costs, making deferred payments appear less salient than immediate debt. This may inflate consumers' perception of available funds at the point of purchase, increasing their propensity to spend (Kumar et al. 2024; Jose et al. 2025; Di Maggio et al. 2022; Waliszewski et al. 2024).

A final relevant concept is payment salience, often referred to as "pain of paying" (Prelec & Loewenstein 1998), which has also been shown to be associated with the use of BNPL services (Jose et al. 2025; Kumar et al. 2024; Guttman-Kenney et al. 2023; Kumar & Nayak 2025). This cognitive state refers to the negative effect of consumers' experience when paying for a good or service. Furthermore, it is suggested that this state is influenced by the degree to which a payment is psychologically salient to the consumer at the time of the transaction. When a payment is more salient, individuals are more aware of the monetary outflow, which strengthens the psychological experience associated with paying. Conversely, when a payment is less salient, the awareness of the cost is reduced, often weakening spending restraint. Payment methods characterised by lower salience are generally understood as those in which the loss of money is less noticeable to the consumer. For example, digital payments are typically perceived as less salient than cash payments, as the transaction does not involve a tangible outflow of money and therefore feels less like an immediate loss (Broekhoff & van der Cruijsen 2024; Relja et al. 2023). Similarly, instalment-based payment structures often shift consumers' attention away from the full price towards smaller and more manageable periodic payments, lowering the perceived financial burden and pain of payment at the point of purchase (Hayashi & Routh 2025; Maesen & Ang 2024; Ashby et al. 2025). As a result, payment methods such as BNPL, characterised by electronic or mobile-based payments and instalment-based payment structures, are suggested to diminish the perceived pain of paying and, in turn, reduce psychological resistance to spending (Jose et al. 2025; Kumar et al. 2024; Guttman-Kenney et al. 2023; Kumar & Nayak 2025).

2.4 Literature gap and conceptual framework

While prior research has identified both financial constraints and behavioural biases to be associated with BNPL usage, the relative influence of these factors on BNPL usage frequency has not been sufficiently examined. Existing studies have largely examined the two factors in isolation, focusing either on financial constraints or behavioural mechanisms influencing consumer decision-making. As a result, it remains unclear which set of factors exhibits a more dominant relationship with BNPL usage behaviour.

As earlier discussed, existing studies have predominantly focused on the socio-economic characteristics of BNPL users, emphasising financial constraints and financial fragility as potential financial drivers (e.g., Donou-Adonsou & Leslie-Piper 2025; Aidala et al. 2024; Ji et al. 2023). At the same time, a body of literature highlights the role of behavioural mechanisms, suggesting that BNPL may also influence how costs are perceived and evaluated (e.g., Di Maggio et al. 2022; Jose et al. 2025; Relja et al. 2023).

However, these two streams of literature have largely been developed in isolation, with limited focus on directly comparing the financial and behavioural factors within an integrated framework. This separation creates an important gap, as it remains unclear whether financial necessity or cognitive biases play a more dominant role in shaping consumers' BNPL usage frequency. To address this research gap and provide a deeper understanding of the factors underlying BNPL usage, this study examines the role of cognitive biases and financial necessity. Specifically, the two potential determinants are analysed and compared to assess their relative associations with BNPL usage frequency, which serves as the study's primary dependent variable. Financial necessity is captured through consumers' perceived financial constraints, reflecting the traditional view of BNPL as a liquidity management tool, while cognitive biases are operationalised through five behavioural variables in the empirical analysis: the mental accounting index, present bias index, pain of payment index, narrow bracketing dummy, and instalment preference dummy.

By incorporating both perspectives within a single model, this study enables a comparison of the relative associations between financial and behavioural variables and BNPL usage frequency, thereby contributing to the literature by providing a clearer understanding of the factors underlying BNPL behaviour.

2.5 Hypothesis development

Grounded in prior research, this study proposes three hypotheses: one examining the role of mental accounting, another focusing on financial necessity, and a third comparing the relative associations of behavioural and financial factors with BNPL usage frequency. The first hypothesis is specifically grounded in the concept of mental accounting (Thaler 1985, 2008), operationalised as the mental accounting index in the empirical analysis. As discussed, prior research suggests that individuals tend to mentally categorise and evaluate financial transactions within separate "accounts," rather than assessing their overall financial situation in a holistic manner (Thaler 1985, 2008). In the context of BNPL, this mechanism may lead consumers to perceive purchases as more affordable, thereby increasing their likelihood of using BNPL more frequently. Therefore, Hypothesis 1 is grounded in the assumption that individuals who rely on mental accounting to a greater extent, are more likely to engage in BNPL usage more frequently.

H1: Mental accounting is positively associated with BNPL usage frequency.

Moving on, turning to the second hypothesis concerning financial necessity, prior research conceptualises BNPL as a financial tool primarily used by consumers facing liquidity constraints. By enabling the deferral of payments, BNPL allows individuals to smooth consumption when immediate financial resources are limited (Guttman-Kenney et al. 2023; deHaan et al. 2024). In periods of financial strain, consumers may therefore rely on BNPL to maintain their consumption levels despite short-term budget constraints, aligning payments with expected future income. From this perspective, financial necessity emerges as an important potential driver of BNPL usage. Following this line of reasoning, Hypothesis 2 posits that individuals who experience financial necessity to a greater extent, are more likely to engage in BNPL usage more frequently.

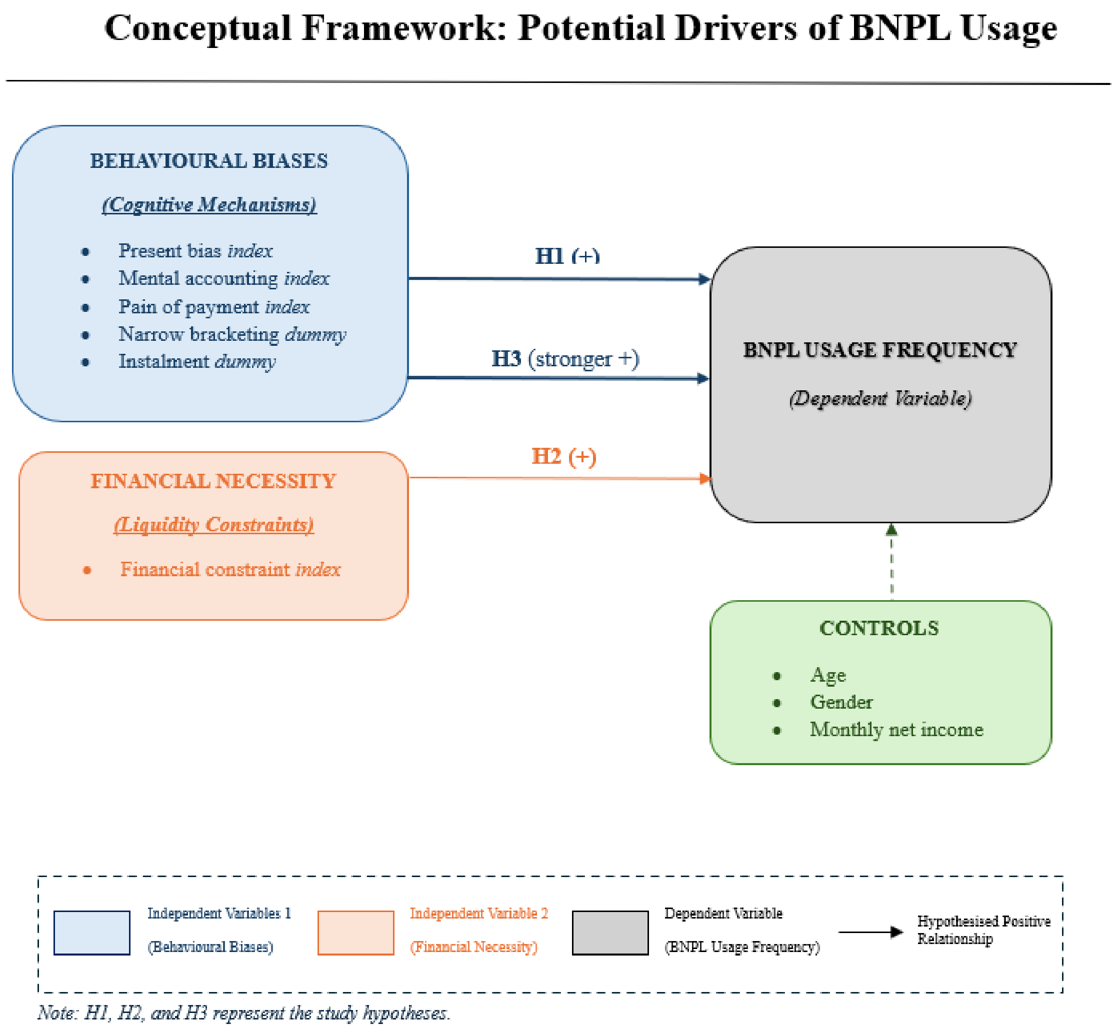
H2: Financial necessity is positively associated with BNPL usage frequency.

Finally, to address the identified gap in prior literature, the third hypothesis examines the relative influence of the financial and behavioural factors associated with BNPL usage. Accordingly, it investigates whether behavioural biases, operationalised through the mental accounting index, present bias index, pain of payment index, narrow bracketing dummy, and instalment preference dummy, exert a stronger positive association with BNPL usage frequency than financial necessity. By incorporating both sets of variables within a single model, this analysis enables a comparison of their relative importance in explaining BNPL usage frequency. Based on prior research highlighting the role of cognitive biases beyond purely financial motives, Hypothesis 3 is formulated on the assumption that behavioural variables may exhibit stronger positive associations with BNPL usage frequency than financial necessity. While H1 focuses specifically on mental accounting, H3 evaluates the broader set of behavioural variables included in the empirical analysis relative to financial necessity.

H3: Behavioural variables have a stronger positive association with BNPL usage frequency than financial necessity.

The conceptual framework presented below summarises the proposed relationships between behavioural biases, financial necessity, and BNPL usage frequency.

Figure 2: Conceptual framework of the hypothesised associations between behavioural biases, financial necessity, and BNPL usage frequency.



3. Methodology

3.1 Research design

This study applies a conclusive, descriptive research design using a single cross-sectional survey. According to Malhotra (2019), a research design is a framework that specifies the procedures necessary for obtaining the information needed to structure or solve research problems. As Malhotra (2019) further outlines, a conclusive approach is appropriate when the aim is "*to describe specific phenomena, test specific hypotheses, and examine specific relationships*", rather than to generate initial exploratory insights. Given that the objective of this study is to deepen the understanding of the financial and behavioural factors underlying the usage of BNPL services, a conclusive research design was chosen. The study builds upon existing theoretical concepts and prior empirical findings and aims to test structured relationships rather than explore an undefined research problem. Furthermore, as data were collected once from a sample of respondents at a single point in time, without involving repeat observations of the same individuals, our research employs a single cross-sectional design, commonly used in descriptive research to measure characteristics of a population and analyse associations between variables at a given point in time.

3.2 Data collection and sampling

3.2.1 Data collection approach

Primary data were collected through a structured, self-administered online survey designed and distributed using Microsoft Forms *(see Figure 3, Appendix)*. Participation was anonymous and voluntary. As Malhotra (2019) highlights, the survey method relies on structured questionnaires administered to a sample of a target population to elicit specific information, such as behaviours, attitudes, intentions, and motivations from participants. Structured questions with predetermined response options were asked along the entire survey, allowing for a straightforward variable coding procedure for subsequent statistical analyses.

An online survey format was selected due to its practical advantages such as cost efficiency, rapid distribution, and consistency in question presentation across respondents. Since all participants receive identical questions and response options, interviewer bias can be eliminated. Furthermore, online surveys may increase comfort of participants and reduce response error related to social desirability, as they allow respondents to complete the questionnaire at a time and place of their choosing (Malhotra 2019).

3.2.2 Questionnaire design

The online survey consisted of the following five sections:

1. Consent and study information
2. BNPL usage and experience
3. Financial attitudes and decision-making I.
4. Financial attitudes and decision-making II.
5. Background information

The structure follows Malhotra's (2019) questionnaire design logic: the survey begins with an informational screen outlining data protection procedures, the purpose of the study, as well as a brief description and a simple visual illustration of BNPL, followed by a mandatory qualifying question asking for consent. Opening questions related to the topic include filter questions that intend to measure participants' familiarity and past experiences with BNPL. Questions gradually move from a general to a more specific nature, investigating information regarding participants' cognitive biases and financial need. Sensitive questions, such as those aiming to elicit classification information for control variables, including participants' age, gender, and income, are placed at the last section of the survey to minimise early survey drop-out and respondent discomfort, as proposed by Malhotra (2019).

The questionnaire consists of a mix of binary and ordinal multiple-choice questions, as well as Likert-scale questions, along with two scenario-based decision tasks. Likert-scale questions were used to measure participants' degrees of agreement with statements related to behavioural tendencies and financial attitudes. Scenario-based decision tasks aimed to capture behavioural responses in realistic purchase contexts, allowing bias constructs, including present bias, mental accounting, and pain of paying, to be observed indirectly through decision-making behaviour. By using a combination of attitudinal and behavioural measures, we aim to reduce reliance on a single measurement approach and consequently strengthen construct validity (Campbell & Fiske 1959; Shen 2017).

3.2.3 Sampling approach

The full sample consisted of 169 participants. Respondents were recruited using snowball sampling, where the survey was initially shared with the authors' direct networks who were encouraged to refer the survey further to their own networks, generating waves of referrals, i.e., a snowball effect. Malhotra (2019) defines snowball sampling as a non-probability sampling technique, where a randomly selected, initial group of participants refers the survey further to subsequent participants, creating waves of responses. This sampling technique was selected for our study because, as Malhotra (2019) notes, snowball sampling is particularly useful in "*locating the desired characteristics in the population*" and it has low sampling costs. Since there is no publicly accessible record of BNPL users, snowball sampling allowed for efficiently locating respondents who are familiar with BNPL services, while it also enabled rapid collection of relevant data within the practical constraints of the thesis context (time, cost, and lack of a comprehensive sampling frame).

3.2.4 Pilot testing

Preceding the official survey launch, the questionnaire was piloted with three individuals. The pilot test aimed to evaluate the logical flow, clarity of wording, general comprehension, and completion time of the survey questions. No major changes, except for two minor alterations, were implemented after the pilot test. The pilot respondents indicated good understanding and completion ability of the survey. As Malhotra (2019) emphasises, pilot testing enhances the reliability and validity of the final questionnaire and reduces measurement error by identifying potential problems before the official, full-scale data collection procedure.

3.2.5 Sampling limitations

While snowball sampling enabled efficient and relevant data collection within the constraints of our study, it also entails several methodological limitations. As Malhotra (2019) outlines, snowball sampling belongs to non-probability sampling techniques, where even if the initial sample of respondents is randomly selected, the final sample usually becomes non-probability because referrals often resemble referrers, rendering the final pool of participants homogeneous. This means that referrals in our sample likely resemble their referrers and display more similar demographic and psychographic characteristics than would occur by chance. Furthermore, as a significant general limitation of non-probability sampling techniques, as noted by Malhotra (2019), the results of our study cannot be generalised in any way to the broader population, since the "*probability of selecting any element for inclusion in the sample*" cannot be determined. This means that our findings are not statistically projectable to the broader population and should rather be interpreted as observations applicable only to the sampled respondents.

3.2.6 Data preparation and cleaning

Prior to conducting statistical analysis in SPSS, the dataset was prepared and cleaned in Excel. The cleaning process involved removing irrelevant variables, renaming and labelling variables for clarity, and ensuring consistent coding across all survey responses. All variables were numerically coded, and, where necessary, Likert-scale items were reverse-coded to ensure consistency in scale direction before being aggregated into composite indices.

The dataset was also screened for missing values and incomplete responses. Out of the total 169 respondents, three individuals' observations were excluded from the analysis due to missing information on the gender and income variables, which were required for the implementation of statistical analyses performed on the dataset and for the inclusion of control variables in regression analyses. The final dataset used for analysis therefore consisted of n =166 respondents. Given the small number of excluded observations, this preparatory step is not likely to materially affect the results.

3.3 Variables

This section aims to describe the dependent, independent, and control variables that we applied in our empirical analysis. All variables were constructed from responses obtained in the structured online survey and were subsequently coded and processed for statistical analysis in Excel and SPSS. A summarised overview of all variables and their respective conceptual foundations is provided in *Table 1 (see Appendix)*.

3.3.1 Dependent variables

Two dependent variables were constructed to capture BNPL usage frequency and BNPL adoption.

The primary dependent variable is BNPL usage frequency, which measures how often participants use BNPL as a payment method. This variable is based on an ordinal scale derived from survey responses (1 = Never; 2 = Rarely; 3 = Sometimes; 4 = Often; 5 = Always when possible), capturing self-reported behavioural frequency (*see Q4, Survey script, Appendix)*, consistent with standard practices in survey-based measurement (Malhotra 2019). It represents the primary outcome variable in subsequent regression models as it allows for capturing the variation in the intensity of BNPL usage across respondents, which has been operationalised as a key outcome variable in prior research examining determinants of BNPL use (Donou-Adonsou & Leslie-Piper 2025).

Additionally, a secondary dependent variable, BNPL usage (dummy-coded), was constructed to measure whether respondents have ever adopted using BNPL as a payment method *(see Q2, Survey script, Appendix)*. This variable is binary and takes the value of 1 if the respondent has used BNPL and 0 if not (1 = Yes; 0 = No). The variable is used as a robustness check to examine if BNPL adoption is influenced differently by the independent variables compared to BNPL usage frequency.

3.3.2 Independent variables

The independent variables are grouped into two categories: financial variables, which intend to measure the degree of financial necessity that respondents demonstrate, and behavioural variables, which measure respondents' cognitive biases including tendencies of mental accounting, present bias, and pain of payment.

3.3.2.1 Financial variable

Financial constraint index

The financial independent variable is represented by the financial constraint index, which measures the extent to which respondents experience limitations in their financial resources. The index is conceptually grounded in literature on financial necessity and financial fragility, capturing both objective (e.g., income constraint) and subjective (e.g., financial stress) dimensions of financial strain (Næser Seldal & Nyhus 2022; Nasir et al. 2025; Donou-Adonsou & Leslie-Piper 2025). It is composed of four variables: three different Likert-scale items that measure respondents' ability to cover unexpected expenses, their experience of financial stress in daily life, and their tendency to run out of money (*see Q11, Survey script, Appendix)*. The fourth component variable is income constraint, which is derived from respondents' monthly net income measure *(see Q15, Survey script, Appendix)*, reverse-coded into an income constraint variable, reflecting the logic that higher net income indicates lower financial constraint and vice versa. The financial constraint index hence represents the average of its four component variables where greater values indicate higher financial stress among participants.

3.3.2.2 Behavioural variables

Behavioural independent variables include three indices representing mental accounting, present bias, and pain of payment, and two dummy-coded binary variables also measuring mental accounting and pain of payment tendencies derived from behavioural scenario questions. These constructs are grounded in behavioural economics and consumer decision-making literature, reflecting systematic deviations from rational financial behaviour.

Mental accounting index

The mental accounting index measures the extent to which respondents compartmentalise financial resources and treat money differently depending on its source and intended use, consistent with mental accounting theory (Thaler 1985, 2008). The index is composed of two Likert-scale items measuring respondents' tendency to think of their expenses in different categories and to think of instalment payments as enablers of keeping money and spending it on additional purchases *(see Q8, Survey script, Appendix)*. The index represents the average numeric score of its two components where higher values indicate greater mental accounting bias among respondents.

Present bias index

The present bias index measures respondents' tendency to apply hyperbolic discounting and overweight immediate benefits relative to future costs, consistent with behavioural economics literature on time-inconsistent preferences (Meier & Sprenger 2010; Kuchler & Pagel 2018; Laibson 1997; O'Donoghue & Rabin 1999). It is composed of four Likert-scale items measuring respondents' tendency to buy on impulse and delay cost, their indicated difficulty to stick to a spending plan, and preference for spending money now rather than saving it for later *(see Q7, Survey script, Appendix)*. The index represents the average score of its four components where higher values indicate greater present bias among respondents.

Pain of payment index

The pain of payment index measures respondents' psychological discomfort associated with spending money, and it is conceptually grounded in the "pain of paying" framework (Prelec & Loewenstein 1998). It is composed of two Likert-scale items measuring respondents' comfort with paying the full price of a product upfront versus in instalments *(see Q8, Survey script, Appendix)*. The index represents the average score of its two components where higher values indicate greater pain of payment associated with paying upfront compared to paying in instalments.

Narrow bracketing dummy

The narrow bracketing dummy variable is also intended to measure mental accounting tendencies among participants, however, due to its binary nature it could not have been incorporated among the ordinal Likert-scale components of the mental accounting index. The variable is derived from a behavioural scenario question (*see Q9, Survey script, Appendix)* in which respondents were asked to evaluate a purchase of 1600 SEK paid in four instalments of 400 SEK each, within the context of a predefined monthly "fun spending" budget. Specifically, respondents indicated whether they would mentally account for the purchase as a total cost of 1600 SEK or as a monthly expense of 400 SEK. The variable takes the value of 1 if the respondent answered 400 SEK, displaying narrow bracketing behaviour, and 0 if their answer was 1600 SEK (1 = 400 SEK; 0 = 1600 SEK). The higher value indicates greater narrow bracketing tendency among respondents.

Instalment dummy

In a similar vein, the instalment dummy variable captures pain of payment (Prelec & Loewenstein 1998) tendencies among participants, however, due to its binary nature it could not be included among the ordinal Likert-scale components of the pain of payment index. It is conceptually grounded in Maesen & Ang's (2024) and Ashby et al.'s (2025) findings that BNPL instalments are associated with increased purchase frequency and larger purchase amounts. It is derived from a behavioural scenario question *(see Q10, Survey script, Appendix)* which asks respondents to choose if they preferred paying for a new pair of headphones upfront or in instalments. The variable takes the value of 1 if participants chose the instalment payment option and 0 if they chose the upfront payment of the full price (1 = I pay 250 SEK monthly for four months; 0 = I pay 1000 SEK now). Higher values indicate a stronger preference for instalment-based payments among participants.

3.3.3 Controls

While the primary regression model in this study aims to capture the direct relationship between financial and behavioural variables and BNPL usage frequency, control variables were introduced in the secondary regression models to control for the impact of alternative, extraneous variables that may influence the dependent variable and confound results (Malhotra 2019). These variables include participants' age, gender, and monthly net income. The age and net income control variables were coded on an ordinal scale, while the gender variable was dummy-coded, as participants involved in the survey indicated only female and male gender types.

3.4 Reliability and factor analysis

To examine the robustness of the constructed variables, reliability and factor analysis (Malhotra 2019) were conducted in SPSS. Internal consistency of the independent variables composing multiple items was assessed using Cronbach's alpha, and factor analysis was applied to examine the underlying dimensionality of the indices.

3.4.1 Reliability analysis and Cronbach's alpha

Results from the reliability analysis, specifically Cronbach's alpha coefficients can be seen for each multi-item construct in *Tables 2-5 (see Appendix).*

With an $\alpha = 0.765$, the present bias index, composed of four items measuring preference for immediate consumption, impulsive spending, and financial planning difficulties, displays good reliability, suggesting a consistent underlying construct.

With $\alpha = 0.671$, standardized $\alpha = 0.704$, the financial constraint index exhibits acceptable reliability. This value indicates that overall, the index captures a common dimension of experienced financial strain among respondents. The slightly lower raw alpha value hints at some variation across the composite items, which combine both objective (e.g., income constraint) and subjective (e.g., financial stress) perceptions of financial constraint, which may introduce some heterogeneity to the ultimate construct.

With $\alpha \approx 0.60$, the pain of payment index exhibits borderline acceptable reliability. Although the value is below the conventional 0.70 threshold (Hair et al. 2019; Malhotra 2019), it can be considered sufficient for our analysis considering the small number of composite items and the exploratory nature of the construct, where values of 0.60 are deemed acceptable (Hair et al. 2019).

The mental accounting index, however, exhibits very low internal consistency ($\alpha = 0.041$). This clearly indicates that statistically the two composite items do not form a unidimensional construct. This may be explained by the highly complex and multidimensional nature of mental accounting (Thaler 1985, 2008; Zhang & Sussman 2018; Prelec & Loewenstein 1998), specifically, as the two composite items capture distinct dimensions of the concept: one reflecting the categorisation of expenses into separate mental "buckets" (i.e., "I think of my expenses in different categories (e.g., travel, food, clothing, etc".)), and the other reflecting the perceived fungibility of money and its reallocation across consumption categories (i.e., "Splitting up the full cost of a purchase allows me to keep money to spend on other things."). With that, we acknowledge that the index lacks internal consistency and does not represent a unidimensional construct. However, as both composite items capture two relevant and theoretically grounded dimensions of mental accounting, the index is retained for analysis. Consequently, it is therefore interpreted as an approximation of a broader behavioural tendency rather than a precise latent construct, and the corresponding empirical results are treated with appropriate caution. Furthermore, this limitation is taken into account in the interpretation of findings, particularly when assessing the strength and consistency of the relationship between mental accounting and BNPL usage.

3.4.2 Factor analysis

To further examine construct validity, factor analysis (Malhotra 2019) with Varimax rotation was performed on all multi-item independent variables. Results can be seen in *Tables 6-8 (see Appendix)*.

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = 0.796) and Bartlett's test of sphericity ($p < 0.001$) indicated that the data were suitable for factor analysis. The analysis concluded a four-factor structure, explaining approximately 66.4% of the total variance. The rotated component matrix shows a clear clustering of items into distinct factors.

Most items related to financial constraint load strongly onto a single factor, indicating an overall coherent construct. Similarly, items related to present bias load predominantly onto a separate factor, confirming internal consistency of the construct. The two items representing the pain of payment index also load strongly onto a distinct factor, supporting their validity as a behavioural construct. The two items intended to capture mental accounting load onto different factors, reinforcing the reliability analysis suggesting that mental accounting is not a unidimensional construct, but rather reflects multiple underlying behavioural mechanisms.

Taken together, the factor analysis provides general support for the construct validity of the financial constraint, present bias, and pain of payment indices. It also reinforces the interpretation of mental accounting as a multidimensional and more complex construct, which is partially captured by its two composite items. Consequently, while the mental accounting index is retained for analysis due to its theoretical relevance, its results are interpreted with appropriate caution.

3.5 Regression models

To examine the relationship between the financial and behavioural independent variables and the dependent variable BNPL usage, a series of Ordinary Least Squares (OLS) regression models were estimated where the dependent variable was not binary (i.e., dependent variable = BNPL usage frequency). OLS regression is a widely used statistical model for estimating linear relationships between a dependent variable and multiple explanatory variables (Malhotra 2019; Wooldridge 2009). It estimates parameters by minimising the sum of squared residuals and constitutes the dominant regression technique applied in economic and financial research (Stock & Watson 2020). Furthermore, applying OLS regression in this context is especially useful, as it allows for estimating and comparing the relative effects of financial and behavioural determinants on BNPL usage.

3.5.1 Measurement considerations and model justification

The primary dependent variable, BNPL usage frequency, is measured on an ordinal scale, as noted previously. However, following Carifio & Perla (2008), it is approximated as a continuous variable for the purpose of the OLS regression analyses, since ordinal variables with multiple response categories can reasonably approximate interval-level measurement and are therefore commonly treated as continuous in empirical research.

Similarly, independent variables that represent composite indices, i.e., the financial constraint index, present bias index, mental accounting index, and pain of payment index, are derived from Likert-scale items which are ordinal in nature. However, as Batterton and Hale (2017) reinforce, *"Likert scales… approximate interval data and are therefore amenable to traditional parametric methods"* including OLS regression. Furthermore, Norman (2010) highlights that parametric methods, such as OLS regression, are generally robust to violations of the interval-level assumption and can be applied to ordinal data such as Likert scales "*without concern*."

Hence, treating both the dependent variable and the independent composite indices as continuous is scientifically justified and constitutes a relevant method for the purpose of this study, as it allows the application of the OLS model, which is efficient in estimating linear relationships, facilitates straightforward interpretation of coefficient estimates, and enables the simultaneous inclusion of both continuous and dummy-coded variables (Wooldridge 2009). Alternative models such as ordered logit or ordered probit could also be applied, however, these models estimate coefficients that are not directly interpretable and require additional transformation to obtain meaningful effects. As noted by Gomila (2021), *"the coefficients of nonlinear models are never directly interpretable"*. Given that this study aims to compare the direction and magnitude of relationships across variables, OLS regression is preferred due to its straightforward interpretability.

3.5.2 Binary dependent variable and logistic regression

In addition to the OLS regression models using BNPL usage frequency as the dependent variable, a robustness check was conducted using a binary dependent variable indicating whether respondents have used BNPL. Binary dependent variables require the application of logistic regression models, rather than linear models, since the latter may produce probabilities that fall outside the [0,1] range (Hair et al. 2019; Malhotra 2019; Stock & Watson 2020). The logistic model addresses this limitation by modelling the probability of an outcome occurring as a non-linear function of the independent variables, more specifically, as Malhotra (2019) notes, "*it estimates the probability of an observation belonging to a particular group"*. In the context of this study, the logistic regression model is applied to examine whether the financial and behavioural variables influence the likelihood that an individual adopts BNPL, rather than how frequently they use it. This approach is intended to offer a complementary perspective to the OLS models, which capture variation in BNPL usage frequency. By comparing the results across both model specifications, it is possible to assess the robustness of the identified relationships and to distinguish between factors associated with BNPL adoption and those that primarily affect usage frequency behaviour.

3.5.3 Model specifications

3.5.3.1 OLS regression models

The OLS regression estimations applied in this analysis follow the general multiple regression model (Wooldridge 2009), which can be specified as follows:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \epsilon$$

where, in the context of this study, y denotes the dependent variable BNPL usage frequency, $X_1 \ldots X_k$ denote the independent variables, including the financial, behavioural, and control variables, β_0 is the intercept, $\beta_1 \ldots \beta_k$ are the coefficients associated with each explanatory variable, and ϵ is the error term.

Accordingly, the primary model can be written as:

$$\begin{aligned}\boldsymbol{BNPLFrequency} \\ &= \beta_0 + \beta_1 FinancialConstraintIndex + \beta_2 PresentBiasIndex \\ &+ \beta_3 MentalAccountingIndex + \beta_4 PainofPaymentIndex \\ &+ \beta_5 NarrowBracketingDummy + \beta_6 InstallmentDummy + \epsilon\end{aligned}$$

The secondary model essentially mimics the primary model and adds control variables to it:

$$\begin{aligned}\boldsymbol{BNPLFrequency} \\ &= \beta_0 + \beta_1 FinancialConstraintIndex + \beta_2 PresentBiasIndex \\ &+ \beta_3 MentalAccountingIndex + \beta_4 PainofPaymentIndex \\ &+ \beta_5 NarrowBracketingDummy + \beta_6 InstallmentDummy + \beta_7 Age + \beta_8 Income \\ &+ \beta_9 Gender + \epsilon\end{aligned}$$

3.5.3.2 The logistic regression model

The logistic regression model applied in the case of the binary dependent variable, BNPL adoption, can be generally expressed as follows (Malhotra 2019):

$$log_e\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

where, in the context of this study, p denotes the probability of BNPL adoption, $X_1 \ldots X_k$ represent the explanatory variables, including the financial, behavioural, and control variables, and $\beta_0 \ldots \beta_k$ are the parameters to be estimated.

Thus, the logistic model applied in this study can be specifically expressed as:

$$P(\text{BNPLAdoption} = 1 \mid X) = \frac{\exp(\beta_0 + \beta_1 FinConstraintIndex + \beta_2 PresentBiasIndex + \cdots + \beta_9 Gender)}{1 + \exp(\beta_0 + \beta_1 FinConstraintIndex + \beta_2 PresentBiasIndex + \cdots + \beta_9 Gender)}$$

where BNPL adoption is a binary variable taking the value of 1 if the respondent has used BNPL and 0 if not.

3.5.4 Model estimation strategy

The empirical analysis in this study applies the following stepwise approach:

First, using the primary regression model, the direct relationship between the financial and behavioural variables and BNPL usage frequency was examined excluding control variables. This specification provides an estimate of the unconditional relationship between the dependent and explanatory variables. However, as Wooldridge (2009) notes, it may be subject to omitted variable bias if relevant factors correlated with the dependent and independent variables are not accounted for.

Hence, the second, extended model incorporates demographic control variables, including age, gender, and monthly net income of participants to account for the potential effect of extraneous variables (Malhotra 2019).

Lastly, a third, logistic model is estimated using the binary dependent variable as a robustness check. This enables examining whether the potential determinants of BNPL adoption differ from those influencing usage intensity.

3.6 Additional analyses

In addition to the three regression analyses, descriptive statistics and a correlation analysis were performed to provide an initial overview of the data and to examine relationships between variables prior to regression estimations. These analyses support the interpretation of the regression results, as they provide insights into general patterns and associations within the dataset.

4. Results

4.1 Descriptive statistics

To provide an overview of the key variables in the data, descriptive statistics were performed in SPSS as part of the data analysis process. This section presents the results of descriptive statistics for the final sample (n = 166) and provides initial insights into the distribution, variability, and central tendencies of the variables used in the empirical analysis. An overview of descriptive statistics results can be seen in *Table 9 (see Appendix)*.

The primary dependent variable, BNPL usage frequency, has a mean value of 2.64 on a five-point scale, indicating that respondents use BNPL on average between "rarely" and "sometimes", hinting at an occasional average usage frequency. At the same time, the binary dependent variable, BNPL adoption, has a mean value of 0.73, indicating that approximately 73% of the respondents have used BNPL at least once, suggesting a relatively high level of BNPL adoption in the sample.

Regarding the financial constraint index, the variable has a mean value of 2.1807, derived from the five-point scale Likert statements, which indicates that on average, respondents in the sample do not exhibit high levels of financial constraint. This is further supported by the income distribution within the sample, where the income variable displays a mean value of 3.61 on a five-point scale, with a median of 4 and a mode of 5, further suggesting that the sample is skewed towards higher income categories. Hence, the sample is not dominated by financially vulnerable individuals but rather comprises mostly respondents with moderate to low levels of financial stress. This sample composition can have interesting implications for the interpretation of the relationship between BNPL use and financial constraint, particularly in consideration of the possibility that BNPL usage is not primarily encouraged by financial necessity in the given sample.

Behavioural variables, including mental accounting, present bias, and pain of payment indices, have moderate mean values: 2.774; 2.3148; and 2.075 respectively. This suggests that behavioural biases exist in the sample and vary across respondents, warranting their inclusion as explanatory variables in subsequent analyses.

Lastly, considering demographic variables, the age variable exhibits a mean value of 3.25, indicating that the average respondent falls between the 35-44 and 45-54 age categories and that the sample is not strongly skewed towards either the youngest or oldest respondents. Furthermore, the gender distribution within the sample is also relatively balanced with 47% male and 53% female participants.

Overall, descriptive results suggest that BNPL usage is relatively widespread in the sample, despite moderate levels of financial constraint. This raises the initial assumption that BNPL usage might not be primarily encouraged by financial necessity in the sample but instead may exhibit stronger positive associations with behavioural biases. The sample further displays a balanced demographic profile regarding age and gender, reducing the likelihood that the results are driven by demographic skewness.

4.2 Correlation analysis

To examine the relationships between the variables prior to regression analysis, correlation analysis in SPSS was performed. This section presents the results from the correlation analysis and provides initial insights into the direction and strength of associations between BNPL usage and the explanatory variables. An overview of the correlation matrix can be seen in *Table 10 (see Appendix)*.

Correlation results indicate that BNPL usage is positively correlated with several key behavioural variables. In particular, mental accounting ($r = 0.159$), pain of payment ($r = 0.15$), and instalment preference ($r = 0.173$) all show positive correlation with the BNPL usage frequency variable. These results project that individuals who display stronger behavioural tendencies, specifically tendencies of mental accounting, pain of payment, and instalment preference, are more likely to use BNPL more frequently.

In contrast, the financial constraint index shows the strongest negative correlation ($r = -0.091$) with BNPL usage frequency in the sample. This result may suggest that higher levels of financial constraint are *not* associated with more frequent BNPL usage in the sample. This observation contrasts with existing literature, where the primary narrative assumes a positive association between financial constraint and BNPL use (Consumer Financial Protection Bureau 2025; Chen et al. 2024; Aidala et al. 2025; Guttman-Kenney et al. 2023; Di Maggio et al. 2022; Cornelli et al. 2023). Furthermore, the strongest negative correlation in the overall matrix ($r = -0.518$) is represented by the association between the financial constraint index and the income variable, suggesting support for the validity of the financial constraint index, as higher income levels are associated with lower financial constraint. It also reinforces that the lack of a positive relationship between financial constraint and BNPL usage is not due to measurement error but rather reflects a pattern present in the sample.

Lastly, the strongest positive correlation in the overall matrix ($r = 0.66$) is represented between BNPL usage frequency and BNPL adoption. This expectedly suggests that those who have used BNPL are also more likely to use it more frequently.

4.3 Regression results

4.3.1 Primary OLS regression model

The results of the primary regression model, which estimates the direct, unconditional relationship between BNPL usage frequency and the financial and behavioural independent variables excluding controls, can be seen in *Table 11* (*see Appendix).* While the model has modest explanatory power ($R^2 = 0.089$), the overall model is statistically significant ($F = 2.577$, $p = 0.021$), indicating that the included variables jointly contribute to explaining BNPL usage frequency. No autocorrelation was detected (Durbin-Watson = 2.040). No problematic multicollinearity was observed as the highest condition index was 13.351, which remains below the commonly accepted threshold of 30, above which multicollinearity may be considered problematic (Belsley et al. 1980; Hair et al. 2019). Although some moderate variance proportions were identified for the individual predictors (e.g., values exceeding 0.60), these do not consistently cluster across multiple variables within the same dimension. This suggests that the independent variables do not exhibit problematic linear dependencies. Hence, multicollinearity does not pose a serious threat to the reliability of the estimated coefficients.

Regarding the financial variable, the financial constraint index displays a *negative and statistically significant* relationship with BNPL usage frequency ($\beta = -0.286$, $p = 0.041$). This suggests that individuals in the sample who experience higher levels of financial constraint tend to use BNPL *less* frequently, which contrasts with existing literature that suggests a generally positive relationship between financial constraint and BNPL use (Consumer Financial Protection Bureau 2025; Chen et al. 2024; Aidala et al. 2025; Guttman-Kenney et al. 2023; Di Maggio et al. 2022; Cornelli et al. 2023). Hence, this result does not support H2, which hypothesises a positive relationship between financial constraint and BNPL usage frequency.

Considering the behavioural variables, the mental accounting index shows a *positive and statistically significant* relationship with BNPL usage frequency ($\beta = 0.279$, $p = 0.049$). This indicates that individuals who are more prone to compartmentalising financial decisions are more likely to use BNPL more frequently. These results support H1, which hypothesises a positive relationship between mental accounting and BNPL usage frequency. However, given the previously identified limitations in the internal consistency of the mental accounting index, this result should be interpreted with caution. Similarly, the instalment dummy variable shows a *positive and statistically significant* relationship with BNPL usage frequency (β = 0.688, p = 0.041), indicating that individuals who prefer to pay in instalments are significantly more likely to use BNPL more frequently.

While present bias (β = -0.008, p = 0.953), pain of payment (β = 0.157, p = 0.204), and narrow bracketing (β = -0.103, p = 0.626) do not exhibit statistically significant effects on BNPL usage frequency in this model, the findings indicate that the overall observed effects of certain behavioural variables, particularly mental accounting and instalment preference, support the hypothesised positive relationship with BNPL use in existing literature (e.g., Jose et al. 2025; Maesen & Ang 2024; Ashby et al. 2025; Kumar & Nayak 2025).

Taken together, the results provide partial support for H3. While not all five behavioural variables exhibit statistically significant relationships with BNPL usage frequency, certain behavioural variables, particularly mental accounting and instalment preference, display more consistent positive associations with BNPL usage frequency than the financial constraint index within this sample. However, as noted repeatedly, these findings require a cautious interpretation due to the lack of internal consistency present in the mental accounting index.

4.3.2 Secondary OLS regression model

The results of the second regression model, which mimics the primary model and adds control variables to it, can be seen in *Table 12* (*see Appendix*). Compared to the primary model, the explanatory power marginally increased (R^2 = 0.106), however the adjusted R^2 remained unchanged at 0.054, signalling that the control variables do not substantially improve the model after model complexity is accounted for. The overall model remains statistically significant (F = 2.053, p = 0.037). No autocorrelation was detected (Durbin-Watson = 2.039). The degree of multicollinearity in this model increases moderately compared to the primary model with the highest condition index taking the value of 20.43 yet remaining below the threshold of 30 (Belsley et al. 1980; Hair et al. 2019). Although some higher variance proportions were identified for individual variables, these did not consistently cluster across multiple predictors within the same dimension. Hence, multicollinearity does not pose a serious threat to the reliability of the estimated coefficients in this model either.

The inclusion of demographic control variables leads to some changes in the significance of the explanatory variables. The previously significant effect of financial constraint becomes statistically insignificant ($p = 0.165$), indicating that this relationship is not robust once demographic factors are considered.

The positive effects of mental accounting and instalment preference become slightly weaker, with significance levels increasing to $p = 0.063$ and $p = 0.054$ respectively. While these variables no longer meet the conventional 5% significance threshold, they remain close to significance and continue to exhibit the expected positive direction in coefficients ($\beta = 0.265$ and $\beta = 0.657$ respectively).

Regarding the control variables, namely age, gender, and monthly net income, none of them show a statistically significant effect on BNPL usage frequency ($p = 0.925$, $p = 0.135$, and $p = 0.439$ respectively).

Overall, these results imply that certain behavioural factors, including mental accounting and instalment preference, appear to play a more important role in explaining BNPL usage frequency than demographic characteristics, even though the interpretation of effects in case of the mental accounting index should be accompanied with caution considering the construct's limited internal consistency.

4.3.3 Logistic regression model with binary dependent variable

As a robustness check, a logistic regression model was estimated using the binary dependent variable BNPL adoption. An overview of the results of the logistic regression model is provided in *Table 13 (see Appendix).* The model is not statistically significant overall ($\chi^2 = 12.130$, $p = 0.206$), signalling that the included variables do not jointly explain the likelihood of BNPL adoption. However, the Hosmer-Lemeshow test demonstrates an acceptable fit of the model on the data ($\chi^2 = 8.362$, $p = 0.399$), suggesting no evidence of poor model fit. The explanatory power of the model is modest (Cox & Snell $R^2 = 0.070$; Nagelkerke $R^2 = 0.103$), signalling limited ability to explain variation in BNPL adoption. Overall, this suggests that while the model fits the data adequately, its explanatory power is limited.

The independent variables, pain of payment ($p = 0.084$), income ($p = 0.090$), and gender ($p = 0.062$), approach significance, however none of them meet the 5% threshold. Considering direction, mental accounting and pain of payment show positive relationships with BNPL adoption, while present bias shows a negative relationship with it. However, given the lack of statistical significance, these results should be interpreted with caution.

Overall, these findings contrast with the OLS results and suggest that behavioural and financial factors may have a more relevant connection with the intensity of BNPL usage rather than the initial adoption decision. This highlights that different mechanisms may underlie BNPL adoption versus usage frequency behaviour.

4.4 Summary of hypothesis testing

H1: Mental accounting is positively associated with BNPL usage frequency.	Supported
H2: Financial necessity is positively associated with BNPL usage frequency.	Not supported
H3: Behavioural factors have a stronger positive association with BNPL usage frequency than financial necessity.	Partially supported

5. Discussion

5.1 Key findings

The findings of this study provide several interesting insights into the financial and behavioural factors associated with BNPL usage. First, regression results demonstrate that mental accounting is positively associated with BNPL usage frequency, giving support to H1. Second, financial necessity does not exhibit the expected positive relationship with BNPL usage frequency, resulting in no support for H2. Third, certain behavioural variables, particularly mental accounting and instalment preference, appear to exhibit more consistent positive associations with BNPL usage frequency than financial necessity within the sample, providing partial support for H3. Finally, results from the logistic regression model indicate that neither financial necessity nor behavioural factors significantly explain BNPL adoption, suggesting that different mechanisms might underlie BNPL adoption and BNPL usage intensity.

5.2 Financial necessity and BNPL usage

Contrary to the prevalent narrative in existing literature, which suggests a generally positive relationship between financial necessity and BNPL use (Consumer Financial Protection Bureau 2025; Chen et al. 2024; Di Maggio et al. 2022; Aidala et al. 2025; Guttman-Kenney et al. 2023; Cornelli et al. 2023), the results of this study do not find support for such a relationship. Moreover, results from the primary regression model as well as findings from the correlation analysis indicate a negative relationship between financial constraint and BNPL use, suggesting that more financially constrained individuals tend to use BNPL less frequently, or, in other words, BNPL tends to be used more frequently by less financially constrained individuals within this sample. This finding is interesting from several perspectives.

First, it appears to contrast with the dominant assumption that BNPL serves as a financial coping instrument for liquidity-constrained consumers (Jose et al. 2025; Di Maggio et al. 2022; Consumer Financial Protection Bureau 2025; Guttman-Kenney et al. 2023). Instead, the results imply that BNPL use may be more strongly associated with consumption preferences rather than financial necessity. One possible explanation for this pattern may lie in the composition of the sample, which indicated a skewness towards individuals with moderate to high income levels and relatively low levels of financial stress. In such a context, individuals might be less likely to use BNPL as a tool to bridge liquidity gaps and more likely to have their usage influenced by convenience, flexibility, or behavioural and consumption-related preferences.

Second, this finding may imply that financially constrained individuals might engage in more cautious spending or face more access limitations, for example credit checks, to BNPL services, both of which can reduce their usage frequency. In contrast, financially unconstrained individuals may engage in using BNPL more frequently due to greater flexibility in managing repayments, lower perceived financial risk, and less access limitations to the service.

In sum, these findings suggest that financial necessity does not primarily encourage BNPL use in this sample, and highlight the need for considering alternative explanations, such as behavioural mechanisms in understanding BNPL usage patterns, especially among individuals with relatively low levels of financial strain.

5.3 Behavioural factors and BNPL usage

Results from the regression analyses provide partial support for H3, suggesting that certain behavioural variables, particularly mental accounting and instalment preference, exhibit more consistent positive associations with BNPL usage frequency than financial necessity within the sample. Furthermore, it can also be worthwhile to note that while the financial constraint index loses significance once controls are included in the model, the key behavioural variables, including mental accounting and instalment preference, remain close to the conventional significance threshold and retain their positive direction. However, it is important to note that the interpretation of the mental accounting variable should be treated with caution, given the previously identified limitations in its internal consistency and dimensionality. Despite this, the consistent direction of the relationship across model specifications suggests that underlying behavioural mechanisms related to mental accounting may still play a meaningful role in shaping BNPL usage behaviour.

These findings imply that BNPL usage might not be positively associated with financial need in the sample, but rather with human cognitive mechanisms and biases that shape how consumers perceive and evaluate payments. In particular, mental accounting allows consumers to segment financial obligations into separate mental compartments, leading them to evaluate instalment payments independently from the total purchase cost. This cognitive mechanism can result in an inflated perception of available funds, increasing perceived affordability, hence encouraging more frequent and larger-value purchases (Kumar et al. 2024; Maesen & Ang 2024; Ashby et al. 2025; Jose et al. 2025). Similarly, instalment-based payment structures often shift consumers' attention away from the full price towards smaller and more manageable periodic payments, lowering the perceived financial burden and pain of payment at the point of purchase (Hayashi & Routh 2025; Maesen & Ang 2024; Ashby et al. 2025). Therefore, BNPL may increase perceived affordability even among financially unconstrained individuals, facilitating a higher usage frequency.

Overall, these findings reinforce that BNPL may not primarily function as a financial instrument for alleviating liquidity constraints within the sample. Instead, it appears to serve as a behavioural tool that alters the psychological experience of paying, which may give additional support to the view that decoupling the moment of consumption from the moment of payment may play an important role in encouraging credit use (Raghubir & Srivastava 2008), including BNPL which is classified as a form of Deferred Payment Credit (DPC) by the Financial Conduct Authority (2026).

5.4 Theoretical implications

The major theoretical contribution of this study is that it integrates two previously distinct streams of research regarding two potential drivers of BNPL use: financial necessity and behavioural biases. While previous studies have predominantly examined BNPL usage either in connection with liquidity concepts and financial fragility (e.g., Aidala et al. 2024; Donou-Adonsou & Leslie-Piper 2025; Ji et al. 2023) or in relation to cognitive biases and distorted cost perception (e.g., Jose et al. 2025; Relja et al. 2023; Juita et al. 2024; Nusir et al. 2026), this study integrates both perspectives within an integrated empirical framework. In doing so, it aims to respond to emerging evidence in BNPL literature suggesting that financial constraints alone are insufficient to explain BNPL usage (Di Maggio et al. 2022; Jose et al. 2025; Relja et al. 2023), and that behavioural mechanisms might also play a key role, rather than treating the two as mutually exclusive, isolated explanations.

Moreover, the findings of the study contrast with the prevailing assumption in prior literature that BNPL is primarily a financial coping mechanism used by financially vulnerable consumers, particularly younger individuals and those with lower creditworthiness (e.g., Aidala et al. 2025; Cornelli et al. 2023; Healy et al. 2025; Di Maggio et al. 2022; Consumer Financial Protection Bureau 2025; Chen et al. 2024). Instead, the results suggest that BNPL tends to be used more frequently by financially unconstrained consumers. While this pattern may partly reflect the composition of the sample, which is skewed towards mid- to high-income individuals, the findings nonetheless indicate that these consumers also engage in relatively frequent BNPL usage. Extending this finding, the results also imply that BNPL usage is not concentrated among younger individuals in the sample, given that the average respondent lies approximately in the 35–44 age category, and most respondents belong to the 45–54 age category. This contrasts with the prevailing characterisation of BNPL as a youth-dominated payment behaviour and instead points towards a broader diffusion across demographic groups.

Furthermore, the findings contribute to the literature on mental accounting by reinforcing its multidimensional nature. The low internal consistency of the mental accounting index suggests that the construct may not operate as a single latent dimension, but rather as a set of related yet distinct cognitive processes, such as categorisation, fungibility perception, and temporal allocation of costs. This observation supports prior theoretical work suggesting that mental accounting is inherently complex and context-dependent (Thaler 1985, 2008; Zhang & Sussman 2018). Accordingly, the study highlights the need for more nuanced and multidimensional operationalisations of behavioural constructs in future research.

Finally, the observed divergence between OLS and logistic regression results suggests that BNPL adoption and BNPL usage frequency may be influenced by different underlying mechanisms. While certain behavioural factors appear more relevant for explaining usage frequency, they do not significantly explain adoption. This distinction contributes to the literature by indicating that initial adoption decisions may be driven by structural or contextual factors, whereas usage intensity is more strongly shaped by behavioural biases.

Overall, this study implies a theoretically integrated and behaviourally informed perspective on BNPL usage, emphasising BNPL's role beyond that of a financial instrument to liquidity-constrained consumers. The findings point out that BNPL may be just as commonly, and potentially even more intensively, used by financially unconstrained individuals as by those facing financial constraints, highlighting that its role may extend beyond that of a liquidity management tool. This also implies that BNPL usage is not confined to financially constrained contexts but instead reflects a more broadly adopted and behaviourally driven payment mechanism that operates across diverse demographic groups and income levels.

5.5 Managerial implications

The findings of this study might carry several implications for practitioners and a range of stakeholders involved in the provision, regulation, and consumption of BNPL services.

First, for BNPL providers and fintech firms, the results suggest that beyond the common perception of financial necessity, behavioural mechanisms and cognitive biases may play an equally important role in influencing BNPL usage. This implies that BNPL providers are not merely offering a financing solution but are actively shaping consumer decision-making through payment design. Prior research shows that payment structures, such as instalment framing and deferred payment timing, can significantly influence consumers' perception of costs and increase spending by reducing the perceived "pain of paying" (Prelec & Loewenstein 1998; Soman 2003).

In the context of BNPL, this behavioural mechanism is further reinforced by the decoupling of consumption and payment, which has been shown to affect spending behaviour and consumer decision-making (Jose et al. 2025; Valenciano et al. 2025; Di Maggio et al. 2022; Relja et al. 2023). Accordingly, BNPL providers can strategically design payment interfaces and communication to enhance perceived affordability and encourage usage. However, these findings also highlight the importance of responsible product design, as such features may lead to unintended consequences such as overspending and underestimation of total costs (Hayashi & Routh 2025; deHaan et al. 2024; Cornelli et al. 2023; Ji et al. 2023). Therefore, providers should consider implementing safeguards such as transparent disclosure of total repayment amounts, reminders of outstanding obligations, and clearer presentation of cumulative costs to support informed consumer decision-making.

Second, for retailers who decide to offer BNPL payment options in collaboration with BNPL providers, the findings show that BNPL is not solely a tool for liquidity-constrained individuals, but that it may also be widely and frequently used by financially non-constrained consumers across various age groups. This implies that offering BNPL as a payment solution can contribute to retailers' profitability by leveraging the spending preferences of those with higher disposable incomes: for example, research from Klarna, a leading provider of BNPL services, demonstrates that *"businesses offering Klarna at checkout generated a 30% increase in conversion and a 41% increase in average order value"* (Stripe 2021). In addition, empirical research further supports that BNPL increases consumer spending and the likelihood of selecting higher-priced options, further reinforcing its role as a demand-enhancing mechanism (Ashby et al. 2025; Ji et al. 2023). Consequently, retailers can strategically integrate BNPL into the customer journey to capitalise on these effects, for instance by displaying instalment prices early in the purchase process, embedding BNPL options directly on product pages, and leveraging BNPL as a tool to reduce cart abandonment and increase transaction completion rates. However, by becoming part of the BNPL ecosystem, retailers should also share responsibility for consumer protection in the field. This means that retailers should not only focus on conversion optimisation, but also actively support transparent communication of payment terms. This includes clearly presenting total costs alongside instalment amounts and avoiding price framing that disproportionately emphasises instalment amounts over total costs, which may distort consumers' perception of affordability

(Ashby et al. 2025; Maesen & Ang 2024). In doing so, retailers can balance commercial benefits with long-term customer trust and satisfaction.

Third, for policymakers and regulators, the results emphasise that policymaking should place an equal emphasis on both the financial and behavioural dimensions of BNPL usage. While traditional regulatory approaches tend to focus on credit risk (e.g., Sveriges Riksbank (Svahn 2023)) and financial vulnerability (e.g., Bank for International Settlements (Cornelli et al. 2023)), the findings of this study highlight the importance of also addressing behavioural risks, such as reduced payment salience and biased human decision-making. This implies that BNPL should be understood not only as a financial product but also as a behavioural one, where the design and presentation of payment options can systematically influence consumer choices. In practice, these concerns are increasingly reflected in regulatory responses. For example, regulators such as the Financial Conduct Authority in the United Kingdom have begun to formally integrate BNPL into regulatory frameworks, announcing that BNPL, classified as Deferred Payment Credit (DPC), will come under formal regulation starting 15 July 2026 (FCA 2026). This regulatory shift encompasses stricter requirements on how BNPL products are disclosed and communicated, ensuring that consumers receive information that enables *"effective, timely and informed decisions"* at the point of borrowing (FCA 2026). Similarly, the revised EU Consumer Credit Directive (CCD2) aims to bring BNPL products under formal regulation *"to ensure increased transparency and better consumer protection,"* while requiring that consumers are clearly informed about the total cost of credit in accessible digital formats (European Union 2023; Ritter-Döring & Đuric 2023). In addition, the prohibition of practices such as pre-ticked boxes reflects increasing regulatory attention to behavioural nudging in digital payment environments. At the national level, Sweden has introduced specific rules governing the presentation of payment options in online checkouts, requiring that non-credit payment methods are displayed first and that credit options are not pre-selected, to prevent consumers from being nudged into unintended borrowing decisions (Sveriges Riksdag 2019).

Overall, the findings of this study suggest that BNPL should be understood as both a financial and behavioural consumption mechanism, implying that providers, retailers, and regulators alike must balance the commercial opportunities associated with BNPL with the responsibility to support transparent, informed, and sustainable consumer decision-making.

5.6 Limitations

Several limitations associated with the present study should be acknowledged when interpreting the findings. These limitations relate to the sampling procedure, measurement validity, methodological design, and statistical power.

First, the study relied on snowball sampling, which constitutes a non-probability sampling method (Malhotra 2019). Since participants were primarily recruited through existing social networks, the sample is likely to be relatively homogeneous in terms of characteristics such as education, age, socioeconomic background, and consumption behaviour. This means that the findings cannot be generalised to the broader population and should instead be interpreted as observations specific to the sampled respondents.

Second, certain limitations are associated with the operationalisation of behavioural constructs, particularly mental accounting. While the construct was theoretically grounded in prior literature (Thaler 1985, 2008), the mental accounting index exhibited limited internal consistency ($\alpha = 0.041$), suggesting that the multidimensional nature of the concept may not have been fully captured through the applied survey items. This indicates that mental accounting may operate through several distinct behavioural mechanisms that are difficult to capture using a limited number of quantitative indicators. Furthermore, the two items included in the index appear to capture different dimensions of mental accounting, namely the categorisation of expenses into separate mental accounts and the perceived fungibility and reallocation of money across consumption categories. While both dimensions are theoretically relevant, combining them into a single index may have reduced measurement precision. In retrospect, using only one theoretically justified item or including the two items separately in the regression analyses would likely have constituted a more appropriate operationalisation strategy. Consequently, findings related to mental accounting should be interpreted with particular caution. In addition, the study relied on self-reported survey responses, which may introduce response bias and inaccuracies in participants' evaluations of their own financial behaviour (Malhotra 2019).

Third, the methodological design of the study imposes certain limitations. Due to the cross-sectional nature of the data, the analysis can only identify associations between variables and does not permit causal conclusions (Malhotra 2019). Furthermore, the use of Ordinary Least

Squares (OLS) regression on an ordinal dependent variable represents a methodological approximation, despite being justified (Carifio & Perla 2008; Batterton & Hale 2017; Norman 2010). Hence, alternative modelling approaches such as ordered logit or ordered probit models could provide additional robustness.

A further limitation relates to the specific form of BNPL reflected in the survey design. Several survey questions and behavioural scenarios were framed around an instalment-based BNPL model, where purchases are repaid through multiple smaller payments over time. However, BNPL services can take different forms, including the deferred payment model, often referred to as the "pay after 30 days" option, which may represent a substantial share of BNPL usage in the Swedish market, where the majority of the survey was conducted. Consequently, some respondents may have answered questions based on instalment-based scenarios that did not fully correspond to their typical BNPL experiences. This mismatch may have influenced how certain questions were interpreted and may have limited the ability of the survey measures to fully capture behavioural mechanisms underlying actual BNPL usage.

Finally, the relatively limited sample size (n = 166) constitutes a further limitation of the study. As Hair et al. (2019) note, sample size substantially affects statistical results and the ability of statistical models to identify significant relationships. In smaller samples, limited statistical power may reduce the likelihood of detecting meaningful effects between variables. Consequently, certain relationships may not have reached conventional levels of statistical significance despite potential underlying associations within the data.

5.7 Future research

In further research on this subject, several areas could be explored in greater depth. In particular, the following areas are suggested for further investigation:

Firstly, future research should further examine the behaviour of financially unconstrained consumers in the context of BNPL services. Existing literature and policy discussions predominantly focus on financially vulnerable BNPL users (e.g., Consumer Financial Protection Bureau 2025; Aidala et al. 2025; Aidala et al. 2024; Cornelli et al. 2023; Chen et al. 2024). However, the findings of this study suggest that financially secure consumers may also engage frequently in BNPL usage. Future studies could therefore investigate the motivations underlying

BNPL usage among financially unconstrained individuals, including the roles of convenience, consumption preferences, and behavioural biases.

Secondly, the findings of this study suggest that different underlying mechanisms may apply to BNPL adoption and BNPL usage frequency. Future research should therefore distinguish more clearly between the factors influencing initial adoption and those shaping continued or frequent usage behaviour. While some consumers may adopt BNPL due to convenience, accessibility, or curiosity, repeated usage may instead be more strongly associated with behavioural, psychological, or lifestyle-related factors. Exploring these distinctions could contribute to a more nuanced understanding of BNPL-related consumer behaviour.

Thirdly, future studies should continue exploring the multidimensional nature of mental accounting and related behavioural constructs. The findings of this study suggest that mental accounting may not represent a single unidimensional construct, but rather a combination of distinct cognitive processes such as categorisation, fungibility perception, and temporal separation of payments. Future research could therefore apply more refined measurement scales, experimental designs, or qualitative approaches to better capture these mechanisms.

Finally, future studies could compare BNPL usage behaviour across countries with different levels of BNPL market maturity, consumer cultures, and regulatory environments. Since Sweden represents one of the most developed BNPL markets globally (Svahn 2023), cross-country comparisons may help identify whether the relative importance of financial and behavioural drivers differs across institutional and cultural contexts.

6. Conclusion

In conclusion, this study examined how behavioural biases and financial necessity are associated with BNPL usage frequency within a single integrated framework. The findings show that behavioural factors, particularly mental accounting and instalment preference, are positively associated with BNPL usage frequency, while financial necessity does not exhibit the expected positive relationship. Moreover, certain behavioural factors appear to have a more consistent influence on BNPL usage frequency than financial necessity within the sample. Finally, neither behavioural factors nor financial necessity significantly explain BNPL adoption, suggesting that different mechanisms may underlie BNPL adoption and usage frequency.

By integrating behavioural and financial perspectives, this study contributes to a more comprehensive understanding of BNPL behaviour and highlights the importance of considering both psychological and financial dimensions when examining BNPL services. The findings also provide implications for fintech firms, retailers, and policymakers regarding the design and regulation of BNPL services. However, due to limitations related to sampling and measurement reliability, the results should be interpreted with caution. Future research could build on these findings by using larger and more representative samples and by further refining behavioural constructs related to BNPL usage.

AI disclosure statement

To support the preparation of this study, artificial intelligence (AI) tools, specifically ChatGPT and Gemini, were used in a limited and supportive capacity. Their primary function was to assist with grammar checking, language refinement, improving the clarity and coherence of written text, and refining academic wording and sentence structure. AI tools were also occasionally used to discuss theoretical and methodological concepts to support the authors' understanding of the subject area. Typical prompts included requests such as: *"improve academic wording," "refine sentence structure," "check grammar and clarity,"* and *"summarise or explain this concept for better understanding"*.

The use of AI-assisted tools contributed to improving the readability, structure, and linguistic precision of the thesis. In particular, the tools were helpful in identifying unclear formulations, improving flow between paragraphs, and supporting the communication of complex concepts in a clearer academic manner.

At the same time, the authors recognised several limitations and risks associated with AI-generated outputs. AI-generated suggestions occasionally lacked source accuracy, oversimplified theoretical concepts, or produced interpretations that were not sufficiently aligned with the academic literature. Therefore, all AI-assisted outputs, references, interpretations, and formulations were independently reviewed, verified, and critically evaluated by the authors before inclusion in the thesis.

All substantive elements of the study, including the research topic, theoretical framework, literature review, research design, survey development, data collection, statistical analysis, interpretation of findings, and conclusions, were developed independently by the authors. AI tools were not used to generate original research ideas, conduct statistical analyses, produce empirical results, or draw conclusions on behalf of the authors.

The authors learned that AI can serve as a useful supportive tool for improving clarity and structure in academic writing, but that critical evaluation and independent academic judgment remain essential throughout the research and writing process. The authors take full responsibility for the content, accuracy, and integrity of the work presented in this study.

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Appendix

Figure 1: Number of BNPL-related publications indexed in Scopus over time (bibliometric analysis, January 2026).

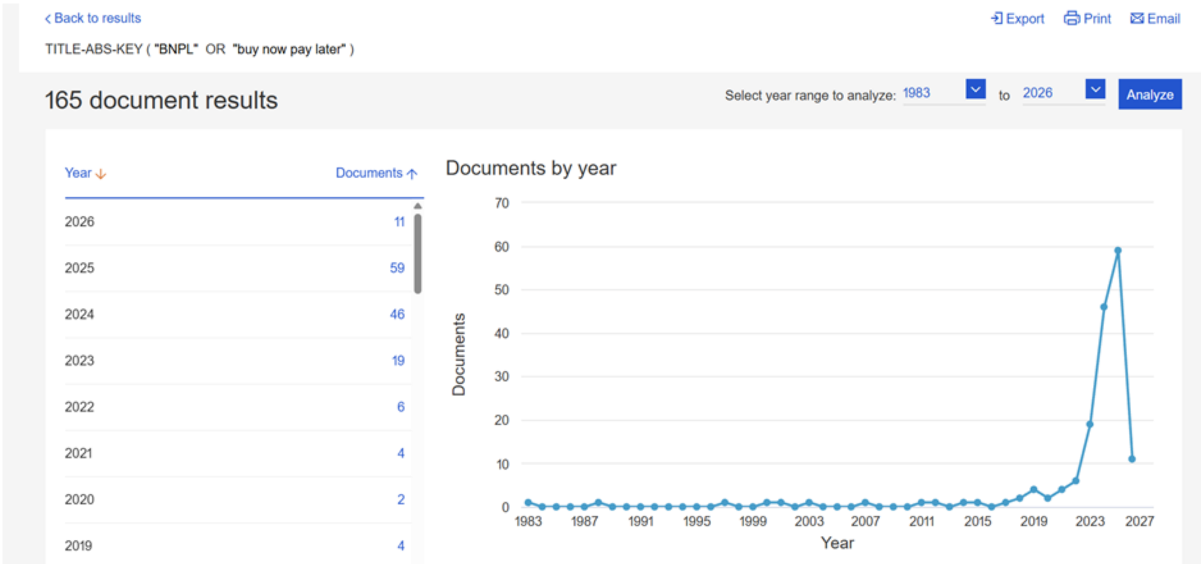


Figure 2: Conceptual framework of the hypothesised associations between behavioural biases, financial necessity, and BNPL usage frequency.

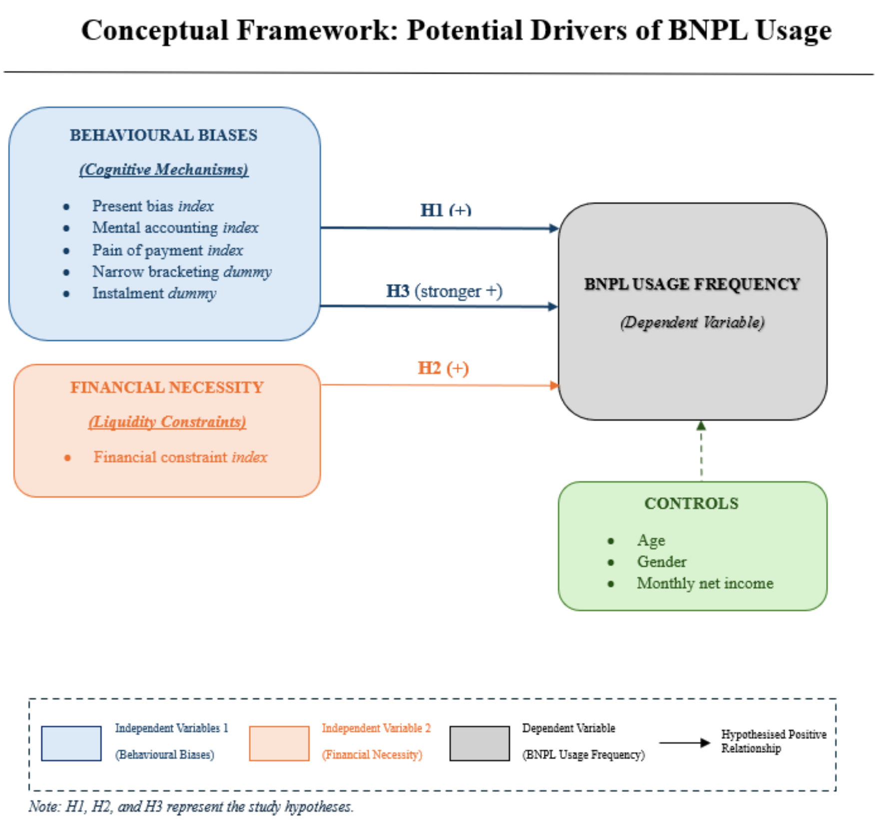


Figure 3: Direct script of the Microsoft Forms Survey

Buy Now, Pay Later (BNPL) Survey Questionnaire

Authors: Ronja Winter (Stockholm School of Economics) Flora Somlai (Stockholm School of Economics)

Consent & Study Information

Consent information
The student's project. As an integral part of the educational program at the Stockholm School of Economics, enrolled students complete an individual thesis. This work is sometimes based upon surveys and interviews connected to the subject. Participation is naturally entirely voluntary, and this text is intended to provide you with necessary information about that may concern your participation in the study or interview. You can at any time withdraw your consent and your data will thereafter be permanently erased.

Confidentiality. Anything you say or state in the survey or to the interviewers will be held strictly confidential and will only be made available to supervisors, tutors and the course management team.

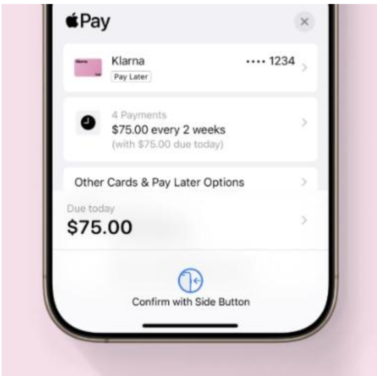
Secured storage of data. All data will be stored and processed safely by the SSE and will be permanently deleted when the projected is completed.

No personal data will be published. The thesis written by the students will not contain any information that may identify you as participant to the survey or interview subject.

Your rights under GDPR. You are welcome to visit https://www.hhs.se/en/about-us/data-protection/ in order read more and obtain information on your rights related to personal data.

Project information

Project title: Buy Now, Pay Later
Year and semester: Year 3, Semester 6 in BSc Retail Management Program
Aim of the study: This study examines attitudes, perceptions, and behaviors related to Buy Now, Pay Later (BNPL) payment services among individuals aged 18 and above. Buy Now, Pay Later (BNPL) is a payment method that allows consumers to receive a product immediately and pay for it later. Depending on the provider, payment may be made in one later payment or spread over several instalments. BNPL services are commonly offered by providers such as Klarna and are frequently available when shopping online. A simple illustration of BNPL can be seen in the picture below.



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Supervisor e-mail address: (Carin.Rehncrona@hhs.se)
Type of personal data processed: Non-sensitive personal data such as responses to questions about financial attitudes and BNPL usage.
The survey takes around 3-5 minutes to complete.

Consent

- I have read the information above and consent to participate in this study.

BNPL Usage & Experience

1. Have you ever heard of Buy Now, Pay Later (BNPL) prior to this survey?

- Yes
- No

2. Have you ever used BNPL payment services (e.g., via Klarna, Apple Pay, etc.)?

- Yes
- No

3. Do you think BNPL is a form of credit (borrowing money)?

- Yes
- No

4. How often do you pay for your purchases by BNPL?

- Never
- Rarely

- Sometimes
- Often
- Always when possible

5. For what types of purchases have you used/would you most likely use BNPL? (Select multiple)

- Clothing/fashion
- Groceries/essentials
- Electronics
- Travel
- Other

6. If you have used BNPL, why have you used it? If you haven't used BNPL, why would you most likely use it? (Select multiple)

- Because I need it. I can't afford the purchase otherwise.
- Because I prefer paying later. However, I could also afford paying upfront.
- Because it feels safer (e.g., protection against fraud or scams).
- Because I prefer to pay the price in instalments.
- Because I have limited access to other credit (e.g., credit card).
- Because it is convenient.
- Other

Financial Attitudes & Decision-Making I-II.

7. Please indicate how much you agree with the following statements:

- I often buy things on impulse.
- I find it difficult to stick to a spending plan.
- If I get extra money, I prefer to spend it now rather than save it for later.
- I sometimes regret purchases I made on impulse.

(Options: Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree)

8. Please indicate how much you agree with the following statements:

- I think of my expenses in different categories (e.g., travel, food, clothing, etc.)

- Splitting up the full cost of a purchase allows me to keep money to spend on other things.
- I am more comfortable with a purchase when the cost is spread over time.
- If I got to pay my 1000 SEK bill next month, I would likely spend 1000 SEK on something else this month.
- Paying the full price at once feels uncomfortable compared to paying in instalments.

(Options: Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree)

9. Imagine, you set yourself a 2000 SEK "fun spending" limit for this month. The same month, you buy shoes for a total of 1600 SEK and you pay in four instalments (400 SEK per month). In your head, how much of your 2000 SEK monthly fun-limit does the purchase use up?

- 1600 SEK
- 400 SEK

10. Imagine, you buy a new pair of headphones for 1000 SEK. At checkout, you are asked to choose between two payment options. Which option do you choose?

- I pay 1000 SEK now.
- I pay 250 SEK monthly for four months.

11. Please indicate how much you agree with the following statements:

- I find it hard to cover unexpected expenses.
- I feel financially stressed in daily life.
- I sometimes run out of money.

(Options: Strongly disagree, Disagree, Neither agree nor disagree, Agree, Strongly agree)

Background Information

12. What is your age?

- 18-24
- 25-34
- 35-44
- 45-54
- 55+

13. What is your gender?

- Woman
- Man
- Non-binary
- Prefer not to say

14. Please choose the option that best describes you.

- Student
- Employed
- Both
- Unemployed
- Other

15. What is the best approximation of your monthly net income? (SEK)

- < 10,000 SEK
- 10,000 - 20,000 SEK
- 20,000 - 30,000 SEK
- 30,000 - 40,000 SEK
- 40,000+ SEK
- Prefer not to say

Table 1: Overview of Variables Used in the Empirical Analysis

Variable	Description	Type	Operationalization/Conceptual grounding
Bnpl_usage_frequency	Ordinal variable measuring how often respondents use BNPL (1 = Never, 5 = Always when possible)	Dependent (Model 1, 2)	Single-item ordinal frequency measure; no index construction required. Captures self-reported usage frequency using ordered response categories (Malhotra 2019). Primary outcome variable based on Donou-Adonsou & Leslie-Piper (2025).
Bnpl_use_dummy (BNPL adoption)	Binary variable indicating whether the respondent has ever adopted using BNPL (1 = Yes, 0 = No).	Dependent (Model 3)	Binary operationalisation of BNPL adoption. Captures whether respondents have ever used BNPL. Suitable for modelling discrete behavioural outcomes in logistic regression (Malhotra 2019).
Financial_constraint_index	Composite index based on Likert-scale items capturing financial stress, liquidity constraints, and income limitations; higher values	Independent	Index constructed as the mean of multiple Likert-scale items. Items were selected to capture complementary dimensions of financial strain (liquidity constraints, financial stress), consistent with prior literature on financial fragility (Nasir et al. 2025; Næser Seldal & Nyhus 2022; Donou-Adonsou

	indicate greater financial constraint		& Leslie-Piper 2025). Internal consistency supported by Cronbach's α = 0.671.
Mental_accounting_index	Composite index measuring the extent to which respondents compartmentalise financial decisions and treat money differently across contexts	Independent	Index constructed from two conceptually distinct but theoretically related items reflecting core dimensions of mental accounting (categorisation of expenses and perceived fungibility of money; Thaler 1985, 2008). Despite low internal consistency (α = 0.041), items were retained due to strong theoretical grounding and multidimensional nature of the construct.
Present_bias_index	Composite index capturing respondents' tendency to prioritise immediate consumption over future financial outcomes	Independent	Composite index calculated as the mean of four items capturing intertemporal preferences favouring immediate over delayed consumption. Grouping is consistent with behavioural economics literature on present bias (Meier & Sprenger 2010; Kuchler & Pagel 2018; Laibson 1997; O'Donoghue & Rabin 1999). High internal consistency (α =

			0.765) supports unidimensionality.
Pain_of_payment_index	Composite index measuring psychological discomfort associated with paying upfront versus in instalments	Independent	Index constructed as the mean of two items capturing psychological discomfort associated with payments. Conceptually grounded in the “pain of paying” framework (Prelec & Loewenstein 1998). Moderate reliability (α ≈ 0.60) acceptable given small number of items
Narrow_bracketing_dummy	Binary variable indicating whether respondents evaluate expenses in isolated parts rather than total cost (1 = narrow bracketing behaviour, 0 = no)	Independent	Binary operationalisation of narrow bracketing behaviour Captures consumers’ tendency to assess financial decisions in isolation rather than as part of total expenditure, consistent with mental accounting theory (Thaler 1999; Koch & Nafziger 2016).
Instalment_dummy	Binary variable indicating preference for instalment payments over full upfront payment (1 =	Independent	Binary operationalisation of preference for instalment-based payments. Captures behavioural preference consistent with payment framing and reduced pain-of-payment mechanisms (Prelec

	instalments, 0 = upfront payment)		& Loewenstein 1998; Maesen & Ang 2024; Ashby et al. 2025).
Age_num	Ordinal variable representing respondent age category	Control	Categorical measurement commonly used in survey research (Malhotra 2019).
Female_dummy	Binary variable indicating gender (1 = female, 0 = male)	Control	Standard demographic variable (Malhotra 2019).
Income_num	Ordinal variable representing monthly net income category	Control	Standard demographic variable (Malhotra 2019).

Table 2: Reliability analysis of the financial constraint index (Cronbach's α)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.671	.704	4

Table 3: Reliability analysis of the present bias index (Cronbach's α)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.765	.764	4

Table 4: Reliability analysis of the mental accounting index (Cronbach's α)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.041	.041	2

Table 5: Reliability analysis of the pain of payment index (Cronbach's α)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.599	.601	2

Table 6: KMO and Bartlett's test of sampling adequacy

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.796
Bartlett's Test of Sphericity	Approx. Chi-Square	646.961
	df	66
	Sig.	<.001

Table 7: Total variance explained by extracted components (PCA, Varimax rotation)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.089	34.075	34.075	4.089	34.075	34.075	2.654	22.116	22.116
2	1.512	12.604	46.679	1.512	12.604	46.679	2.267	18.892	41.007
3	1.336	11.132	57.811	1.336	11.132	57.811	1.937	16.145	57.152
4	1.031	8.588	66.399	1.031	8.588	66.399	1.110	9.247	66.399
5	.930	7.752	74.151						
6	.711	5.923	80.074						
7	.581	4.842	84.917						
8	.477	3.977	88.894						
9	.424	3.531	92.425						
10	.342	2.853	95.279						
11	.306	2.554	97.832						
12	.260	2.168	100.000						

Extraction Method: Principal Component Analysis.

Table 8: Rotated component matrix of independent variables (Varimax rotation)

Rotated Component Matrix[a]

	Component			
	1	2	3	4
income_constraint		.338		.597
lk_unexpected_num	.817		.279	-.157
lk_stress_num	.879			.150
lk_runout_num	.817	.199	.170	
lk_impulse_num	-.144	.820		
lk_planhard_num	.256	.712	.223	
lk_spendnow_num	.400	.685	.148	-.137
lk_delay_spend_num	.438	.562	.203	.227
lk_catgories_num		-.279		.747
lk_keepmoney_num	.295		.719	.121
lk_fullprice_pain_num			.790	
lk_spreadcomfort_num	.108	.206	.748	-.223

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Table 9: Descriptive statistics of key variables

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis		CV
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error	Statistic
bnpl_usage_frequency	166	4	1	5	438	2.64	.100	1.289	1.663	.221	.188	-1.095	.375	48.87
financial_constraint_index	166	3.50	1.00	4.50	362.00	2.1807	.06404	.82509	.681	.559	.188	-.093	.375	37.8357
present_bias_index	166	3.25	1.00	4.25	384.25	2.3148	.06257	.80619	.650	.227	.188	-.747	.375	34.8284
mental_accounting_index	166	3.5	1.0	4.5	460.5	2.774	.0573	.7376	.544	-.090	.188	-.485	.375	26.590
pain_of_payment_index	166	3.5	1.0	4.5	344.5	2.075	.0705	.9089	.826	.496	.188	-.644	.375	43.796
narrow_bracketing_dummy	166	1	0	1	59	.36	.037	.480	.230	.610	.188	-1.648	.375	135.08
instalment_dummy	166	1	0	1	18	.11	.024	.312	.097	2.542	.188	4.515	.375	287.61
income_num	166	4	1	5	600	3.61	.106	1.365	1.863	-.490	.188	-1.176	.375	37.76
female_dummy	166	1	0	1	88	.53	.039	.501	.251	-.122	.188	-2.010	.375	94.43
age_num	166	4	1	5	539	3.25	.120	1.551	2.405	-.401	.188	-1.389	.375	47.76
bnpl_use_dummy	166	1	0	1	122	.73	.034	.443	.196	-1.074	.188	-.856	.375	60.24
Valid N (listwise)	166													

Statistics

	bnpl_usage_frequency	financial_constraint_index	present_bias_index	mental_accounting_index	pain_of_payment_index	narrow_bracketing_dummy	instalment_dummy	income_num	female_dummy	age_num	bnpl_use_dummy
N Valid	166	166	166	166	166	166	166	166	166	166	166
N Missing	0	0	0	0	0	0	0	0	0	0	0
Mean	2.64	2.1807	2.3148	2.774	2.075	.36	.11	3.61	.53	3.25	.73
Median	3.00	2.0000	2.2500	3.000	2.000	.00	.00	4.00	1.00	4.00	1.00
Mode	1	2.00	2.75	3.0	1.0	0	0	5	1	4	1
Std. Deviation	1.289	.82509	.80619	.7376	.9089	.480	.312	1.365	.501	1.551	.443
Variance	1.663	.681	.650	.544	.826	.230	.097	1.863	.251	2.405	.196
Skewness	.221	.559	.227	-.090	.496	.610	2.542	-.490	-.122	-.401	-1.074
Std. Error of Skewness	.188	.188	.188	.188	.188	.188	.188	.188	.188	.188	.188
Kurtosis	-1.095	-.093	-.747	-.485	-.644	-1.648	4.515	-1.176	-2.010	-1.389	-.856
Std. Error of Kurtosis	.375	.375	.375	.375	.375	.375	.375	.375	.375	.375	.375
Minimum	1	1.00	1.00	1.0	1.0	0	0	1	0	1	0
Maximum	5	4.50	4.25	4.5	4.5	1	1	5	1	5	1
Sum	438	362.00	384.25	460.5	344.5	59	18	600	88	539	122

Table 10: Correlation matrix of variables

Correlations

		bnpl_usage_frequency	financial_constraint_index	present_bias_index	mental_accounting_index	pain_of_payment_index	narrow_bracketing_dummy	instalment_dummy	income_num	female_dummy	age_num	bnpl_use_dummy
bnpl_usage_frequency	Pearson Correlation	1	-.091	-.028	.159*	.150	-.026	.173*	.155*	.055	.136	.659**
	Sig. (2-tailed)		.246	.717	.041	.054	.738	.025	.047	.485	.081	<.001
	N	166	166	166	166	166	166	166	166	166	166	166
financial_constraint_index	Pearson Correlation	-.091	1	.465**	.245**	.271**	.166*	.194*	-.518**	.137	-.247**	-.038
	Sig. (2-tailed)	.246		<.001	.001	<.001	.033	.012	<.001	.078	.001	.626
	N	166	166	166	166	166	166	166	166	166	166	166
present_bias_index	Pearson Correlation	-.028	.465**	1	.124	.342**	.234**	.080	-.191*	.083	-.185*	-.020
	Sig. (2-tailed)	.717	<.001		.111	<.001	.002	.303	.014	.286	.017	.803
	N	166	166	166	166	166	166	166	166	166	166	166
mental_accounting_index	Pearson Correlation	.159*	.245**	.124	1	.281**	.040	.094	-.018	-.010	.020	.085
	Sig. (2-tailed)	.041	.001	.111		<.001	.610	.229	.820	.896	.799	.278
	N	166	166	166	166	166	166	166	166	166	166	166
pain_of_payment_index	Pearson Correlation	.150	.271**	.342**	.281**	1	.119	.302**	-.025	-.108	.142	.133
	Sig. (2-tailed)	.054	<.001	<.001	<.001		.127	<.001	.746	.165	.069	.088
	N	166	166	166	166	166	166	166	166	166	166	166
narrow_bracketing_dummy	Pearson Correlation	-.026	.166*	.234**	.040	.119	1	.146	-.141	-.032	-.094	.018
	Sig. (2-tailed)	.738	.033	.002	.610	.127		.061	.070	.680	.227	.816
	N	166	166	166	166	166	166	166	166	166	166	166
instalment_dummy	Pearson Correlation	.173*	.194*	.080	.094	.302**	.146	1	.028	-.060	.145	.034
	Sig. (2-tailed)	.025	.012	.303	.229	<.001	.061		.724	.444	.063	.665
	N	166	166	166	166	166	166	166	166	166	166	166
income_num	Pearson Correlation	.155*	-.518**	-.191*	-.018	-.025	-.141	.028	1	-.187*	.632**	.161*
	Sig. (2-tailed)	.047	<.001	.014	.820	.746	.070	.724		.016	<.001	.038
	N	166	166	166	166	166	166	166	166	166	166	166
female_dummy	Pearson Correlation	.055	.137	.083	-.010	-.108	-.032	-.060	-.187*	1	-.131	.091
	Sig. (2-tailed)	.485	.078	.286	.896	.165	.680	.444	.016		.093	.244
	N	166	166	166	166	166	166	166	166	166	166	166
age_num	Pearson Correlation	.136	-.247**	-.185*	.020	.142	-.094	.145	.632**	-.131	1	.131
	Sig. (2-tailed)	.081	.001	.017	.799	.069	.227	.063	<.001	.093		.092
	N	166	166	166	166	166	166	166	166	166	166	166
bnpl_use_dummy	Pearson Correlation	.659**	-.038	-.020	.085	.133	.018	.034	.161*	.091	.131	1
	Sig. (2-tailed)	<.001	.626	.803	.278	.088	.816	.665	.038	.244	.092	
	N	166	166	166	166	166	166	166	166	166	166	166

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 11: OLS regression results – BNPL usage frequency (primary model)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.298[a]	.089	.054	1.254	2.040

a. Predictors: (Constant), instalment_dummy, present_bias_index, mental_accounting_index, narrow_bracketing_dummy, pain_of_payment_index, financial_constraint_index

b. Dependent Variable: bnpl_usage_frequency

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.308	6	4.051	2.577	.021[b]
	Residual	250.005	159	1.572		
	Total	274.313	165			

a. Dependent Variable: bnpl_usage_frequency

b. Predictors: (Constant), instalment_dummy, present_bias_index, mental_accounting_index, narrow_bracketing_dummy, pain_of_payment_index, financial_constraint_index

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	financial_constraint_index	present_bias_index	mental_accounting_index	pain_of_payment_index	narrow_bracketing_dummy	instalment_dummy
1	1	5.313	1.000	.00	.00	.00	.00	.00	.01	.01
	2	.844	2.508	.00	.00	.00	.00	.00	.01	.86
	3	.562	3.074	.00	.00	.00	.00	.01	.95	.03
	4	.107	7.060	.00	.23	.03	.00	.77	.01	.04
	5	.085	7.920	.08	.12	.21	.29	.11	.02	.02
	6	.059	9.461	.04	.64	.60	.00	.10	.01	.05
	7	.030	13.351	.88	.00	.16	.70	.01	.00	.00

a. Dependent Variable: bnpl_usage_frequency

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.146	.458		4.685	<.001	1.241	3.050					
	financial_constraint_index	-.286	.139	-.183	-2.062	.041	-.561	-.012	-.091	-.161	-.156	.726	1.378
	present_bias_index	-.008	.144	-.005	-.059	.953	-.293	.276	-.028	-.005	-.004	.705	1.419
	mental_accounting_index	.279	.140	.159	1.983	.049	.001	.556	.159	.155	.150	.888	1.127
	pain_of_payment_index	.157	.123	.111	1.276	.204	-.086	.401	.150	.101	.097	.758	1.318
	narrow_bracketing_dummy	-.103	.211	-.038	-.488	.626	-.520	.314	-.026	-.039	-.037	.927	1.079
	instalment_dummy	.688	.334	.167	2.059	.041	.028	1.349	.173	.161	.156	.876	1.141

a. Dependent Variable: bnpl_usage_frequency

Table 12: OLS regression results with control variables (secondary model)

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.325[a]	.106	.054	1.254	2.039

a. Predictors: (Constant), age_num, mental_accounting_index, narrow_bracketing_dummy, female_dummy, instalment_dummy, present_bias_index, pain_of_payment_index, financial_constraint_index, income_num

b. Dependent Variable: bnpl_usage_frequency

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	29.051	9	3.228	2.053	.037[b]
	Residual	245.263	156	1.572		
	Total	274.313	165			

a. Dependent Variable: bnpl_usage_frequency

b. Predictors: (Constant), age_num, mental_accounting_index, narrow_bracketing_dummy, female_dummy, instalment_dummy, present_bias_index, pain_of_payment_index, financial_constraint_index, income_num

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions									
				(Constant)	financial_constraint_index	present_bias_index	mental_accounting_index	pain_of_payment_index	narrow_bracketing_dummy	instalment_dummy	income_num	female_dummy	age_num
1	1	7.475	1.000	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
	2	.892	2.895	.00	.00	.00	.00	.00	.03	.73	.00	.03	.00
	3	.611	3.497	.00	.00	.00	.00	.00	.80	.09	.00	.00	.01
	4	.472	3.982	.00	.00	.00	.00	.00	.00	.06	.01	.71	.02
	5	.256	5.406	.00	.06	.03	.00	.04	.13	.01	.04	.15	.09
	6	.099	8.696	.01	.07	.01	.02	.84	.00	.05	.01	.07	.01
	7	.074	10.078	.00	.23	.22	.00	.00	.01	.03	.15	.00	.40
	8	.069	10.409	.01	.02	.35	.42	.01	.01	.00	.00	.00	.16
	9	.035	14.719	.04	.31	.38	.45	.09	.00	.01	.30	.00	.29
	10	.018	20.429	.94	.31	.00	.11	.00	.01	.02	.48	.03	.02

a. Dependent Variable: bnpl_usage_frequency

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.576	.636		2.478	.014	.319	2.832					
	financial_constraint_index	-.229	.164	-.147	-1.394	.165	-.554	.095	-.091	-.111	-.106	.518	1.931
	present_bias_index	-.030	.148	-.019	-.205	.838	-.322	.262	-.028	-.016	-.016	.670	1.492
	mental_accounting_index	.265	.141	.152	1.875	.063	-.014	.544	.159	.148	.142	.876	1.142
	pain_of_payment_index	.173	.127	.122	1.360	.176	-.078	.424	.150	.108	.103	.712	1.404
	narrow_bracketing_dummy	-.064	.213	-.024	-.302	.763	-.484	.356	-.026	-.024	-.023	.914	1.094
	instalment_dummy	.657	.339	.159	1.939	.054	-.012	1.327	.173	.153	.147	.853	1.172
	income_num	.084	.108	.089	.775	.439	-.130	.298	.155	.062	.059	.437	2.291
	female_dummy	.303	.202	.118	1.503	.135	-.095	.701	.055	.119	.114	.936	1.069
	age_num	.008	.085	.010	.095	.925	-.161	.177	.136	.008	.007	.543	1.840

a. Dependent Variable: bnpl_usage_frequency

Table 13: Logistic regression results – binary dependent variable: BNPL adoption

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	179.860[a]	.070	.103

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.362	8	.399

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	12.130	9	.206
	Block	12.130	9	.206
	Model	12.130	9	.206

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	financial_constraint_index	.070	.316	.049	1	.825	1.072	.577	1.992
	present_bias_index	-.238	.285	.697	1	.404	.788	.451	1.378
	mental_accounting_index	.157	.272	.331	1	.565	1.170	.686	1.996
	pain_of_payment_index	.439	.254	2.994	1	.084	1.551	.943	2.551
	narrow_bracketing_dummy	.240	.401	.357	1	.550	1.271	.579	2.789
	instalment_dummy	-.145	.662	.048	1	.827	.865	.237	3.165
	income_num	.349	.205	2.878	1	.090	1.417	.947	2.120
	female_dummy	.713	.383	3.473	1	.062	2.041	.964	4.321
	age_num	-.013	.157	.007	1	.934	.987	.726	1.342
	Constant	-1.503	1.189	1.599	1	.206	.222		

a. Variable(s) entered on step 1: financial_constraint_index, present_bias_index, mental_accounting_index, pain_of_payment_index, narrow_bracketing_dummy, instalment_dummy, income_num, female_dummy, age_num.