How Complex Are Financial Decisions? Evidence from Credit Card Choice

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Complexity is increasingly recognized as a barrier to sound financial decision-making, yet no theoretical framework currently characterizes it. We propose a framework that quantifies the complexity of financial decisions based on their computational demands and apply it to binary credit card choices. Using a combined behavioral and eye-tracking experiment, we show that complexity, rather than inattention or limited financial literacy, drives mistakes, and that it disproportionately burdens cardholders who carry a balance, for whom the stakes are highest. Our findings suggest that complexity is a fundamental barrier to optimal financial decision-making, even in seemingly simple choices.

Credit card borrowing imposes a significant financial burden on U.S. households. In 2025, outstanding credit card debt exceeded $1.23 trillion, with delinquency rates of 12.4 percent, the highest among major types of household debt (Federal Reserve Bank of New York, 2025). Households pay around $130 billion per year in borrowing costs (Consumer Financial Protection Bureau, 2023), of which 80 percent stems from interest charged at average rates above 22 percent (Martinez and Seikel, 2024). Much of these costs could be easily avoided by searching for or switching to better options, or allocating purchases and repayments to lower-rate options. Yet many households fail do so, even when faced with only two options (Agarwal et al., 2015; Ponce, Seira and Zamarripa, 2017), raising two key questions: What drives the complexity of credit card choices? And to what extent does this complexity constitute a fundamental barrier to optimal choice?

To address these questions, we apply a computational complexity framework to quantify the

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complexity of credit card choices and test its implications using a combined behavioral and eye-tracking experiment. Specifically, we define complexity as the computational resources required to determine the optimal choice, measured by the number of elementary computations involved.

In consumer problems, complexity generally arise from three sources: the product (e.g., features or pricing structures), the consumer (e.g., consumption and borrowing behaviors or feature preferences), and/or the decision environment (e.g., number of options or distribution channels). While prior literature examines these sources in isolation and typically relies on intuitive measures such as the number of features or options, our framework offers a unified and systematic approach to quantify complexity. This framework is grounded in computational complexity theory, a mathematical framework for studying computational resource requirements (Murawski and Bossaerts, 2016), and the notion of bounded rationality, which recognizes that humans are constrained by limited cognitive resources (Simon, 1955).

In this study, we focus on the initial selection of a credit card contract, as subsequent purchasing and repayment decisions are constrained by this choice. We model credit card choice as consumers choosing the credit card that maximizes their expected value of use over the next 12 months, given the card's features and their expected usage. For simplicity, we characterize a credit card by its two key features: an annual fee and an annual purchase rate (hereinafter, interest rate), where the card's value is proportional to the sum of its annual fee and the total expected interest payments over the year. All other features, such as the value of interest-free borrowing, are held constant. This allows us to then categorized credit cards into three commonly observed types: those with only an annual fee (*fee-only*), only an interest rate (*rate-only*), and those featuring both (*fee-rate*).

We further assume deterministic card usage and equal salience of both card features. By removing uncertainty and salience manipulation, we offer a complexity-based account of behavioral anomalies observed in credit card decision-making previously attributed to present bias (Laibson, 1997; Meier and Sprenger, 2010), overconfidence (Agarwal et al., 2015; Ausubel, 1991), exponential growth bias (Stango and Zinman, 2009), or inattention (Agarwal et al., 2013; Ponce, Seira and Zamarripa, 2017).

We show that decision complexity is driven by the amount of interest computations involved in choosing the optimal card, which depends on two factors: (1) the number of rate-bearing options in the choice set and (2) the consumer's borrowing behavior over 12 months. As either factor increases, so do the computational demands of valuation. Importantly, cardholders who carry a balance—*revolvers*—face (weakly) greater complexity than those who always repay in full—*transactors*—when choosing credit cards, as they must account for interest payments when valuing rate-bearing cards, while *transactors* only need to consider annual fees.

We then test how this complexity affects financial decision-making in a combined behavioral and eye-tracking experiment using card offerings sampled from the market. Financial decision-making is measured by choice quality, cognitive effort, information acquisition, and perceived difficulty in the credit card choices. Each binary choice varies along the two complexity dimensions: (1) the composition of card features in a decision and (2) the number of interest compounding periods over 12 months, along with two additional parameters that capture noisy information processing rather than inherent decision complexity: (3) the presentation of digits in monthly card usage and (4) the similarity of option values.

In the study, 25 participants completed 41 randomly ordered binary credit card decisions and were incentivized to choose the card that minimize total borrowing cost given a deterministic card usage pattern. They then completed a questionnaire capturing demographics, real-life credit card usage, and financial, debt, and risk literacy, as well as numeracy.

We find that the complexity of credit card decisions, particularly card usage, negatively impacts financial decision-making. As complexity increased, participants made more mistakes, exerted more effort, made more eye movements, and perceived the decision as more difficult. Specifically, participants always chose correctly when acting as *transactors* but not when acting as *revolvers*. In the latter case, their decisions became increasingly noisy as computational demands increased, even as they directed more attention to the complexity-relevant feature, that is, interest rates. This highlights that *transactors* and *revolvers* face fundamentally different decision complexity, and that mistakes are driven primarily by complexity rather than inattention or lack of information acquisition.

Beyond complexity, our results show that value similarity exacerbates the impact of complexity on choice quality, suggesting that existing card features may be parameterized to reduce option differentiability and induce mistakes, particularly for *revolvers* who inherently face greater complexity when choosing cards and for whom mistakes are most costly. Consistent with this interpretation, our simulations show that many card offerings in the market yield similar borrowing costs under various borrowing conditions.

We also find that visual features can distort perceived difficulty and bias decision-making. Even when computational demands and response times were similar, participants perceived more visually complex digits (e.g., $1,800 compared to $1,000) as more difficult and were more likely to err when comparing *fee-only* to *rate-only* cards than comparing the former to *fee-rate* options. These results suggest that consumers are sensitive to visual cues, and that product simplification (e.g., offering *fee-only* cards) may not always improve choice quality when alternatives remain complex or difficult to compare.

Lastly, individual sophistication, measured by financial, debt, and risk literacy and numeracy, was positively correlated with perceived difficulty but not with choice quality or cognitive effort. This suggests that even seemingly simple financial decisions, such as choosing between two credit cards (Agarwal et al., 2015), may exceed consumers' cognitive capacities, raising concerns about the effectiveness of financial education and disclosure in improving financial decision-making (Campbell, 2016; Seira, Elizondo and Laguna-Müggenburg, 2017).

While our empirical work focuses on a simplified setting with binary credit card choices, deterministic usage patterns, and a small sample of university students, it demonstrates how the structural properties of consumer problems give rise to observable decision errors. Importantly, the fact that even highly educated and financially literate participants struggle in this environment highlights the need to address complexity in financial decision-making.

Our paper contributes to several strands of literature. We add to the literature on credit card choice anomalies by identifying when deviations stem from cognitive constraints rather than behavioral biases. In easy decisions, mistakes likely reflect behavioral biases: Agarwal et al. (2015) show that wealthy cardholders, who often incur zero interest charges, choose suboptimally because they are inattentive to low-salience features. In contrast, when decisions are complex, mistakes are likely driven by complexity. Our study shows that attentive *revolvers* still make mistakes even in the absence of uncertainty or salience manipulation, ruling out behavioral explanations based on present bias (Laibson, 1997; Meier and Sprenger, 2010), overconfidence (Agarwal et al., 2015; Ausubel, 1991), and inattention (Agarwal et al., 2013; Ponce, Seira and Zamarripa, 2017). Additionally, these deviations cannot be fully explained by rounding or exponential growth bias, that is, linearizing exponential functions (Stango and Zinman, 2009), since they persist even where such heuristics predict same choices.

Our work also relates to the growing literature on complexity in economic decision-making and its implications for competition and product design. Existing studies often use intuitive notions of complexity, such as the number of features or products, type of pricing structure, or contract readability (Celerier and Vallee, 2013) but lack a principled approach to quantifying the complexity of consumer problems and identifying the structural properties that drive complexity, and how it hinders optimal decision-making. We formally quantify the complexity of consumer problems based on computational complexity theory by measuring the computational resources required to make optimal choices (Gilboa, Postlewaite and Schmeidler, 2021). Prior experimental studies using canonical tasks show that decision quality deteriorates with computational demands (Bossaerts and Murawski, 2017; Enke, Graeber and Oprea, 2025; Franco et al., 2022; Murawski and Bossaerts, 2016; Oprea, 2020). Our paper contributes by examining practical-case complexity and its impact on choice behaviors, highlighting that even tractable, everyday financial decisions may exceed consumers' cognitive capacities. This has important market implications, as firms can manipulate complexity through obfuscation and product design to exploit cognitively constrained consumers (Carlin, 2009; Gabaix and Laibson, 2006; Grubb, 2015; Consumer Financial Protection Bureau, 2023). Our work is closely related to Gabaix and Graeber (2024), who measure complexity (more precisely, subjective difficulty) based on the amount of cognitive effort required to make a decision. While their model depends on the consumer's decision strategy and attention allocation, our framework remains agnostic about them and instead characterizes complexity in terms of the computational demands required by an algorithm to solve the problem.

Finally, we contribute to the debate on the effectiveness of financial education and disclosure in improving financial decision-making. While it is well documented that consumers with lower financial literacy are more likely to hold more debt, make only minimum repayments, and pay avoidable fees, highlighting a need for better financial disclosure and education (Lusardi and Tufano, 2015; Stango and Zinman, 2009), these interventions often fail to improve financial outcomes (Campbell, 2016; Seira, Elizondo and Laguna-Müggenburg, 2017). For example, Bar-Gill and Bubb (2012) show that Americans continue to face sticky credit card interest rates and accumulating debt even after the enactment of the CARD (Credit Card Accountability Responsibility and Disclosure) Act in 2009, which aimed to improve disclosure and limit financial costs for consumers. Given that these mistakes are often correlated with other domains of consumer finance, such as investment and mortgage decisions (Agarwal et al., 2009), it is crucial to understand when and how the computational demands of financial decisions exceed consumers' cognitive capacities. (e.g., Campbell, 2016; Carlin, 2009).

The remainder of this article is structured as follows: Section I describes the credit card choice problem and the framework used to operationalize complexity; Section II outlines the experimental design and estimation strategies used for data analysis; Section III presents the main behavioral and eye-tracking results of this study; Section IV discusses the implications of our findings; and lastly, Section V concludes.

I. Conceptual Framework

A. *Choosing credit cards*

We model credit card choice as consumers choosing the credit card that maximizes their expected value of use over the next 12 months, given the card's features and their expected usage. For a given consumer, the expected value of a credit card is equal to the expected monetary benefits of accessing interest-free credit minus the expected borrowing costs, which consists of the annual fee and total expected interest charges over the next 12 months. For simplicity, we characterize each card by its two key features: an annual fee and an annual interest rate, and assume that consumers' future card usage is deterministic.

More formally, let $u = \langle\langle s_1, p_1\rangle, ..., \langle s_{12}, p_{12}\rangle\rangle$ be a consumer's *credit card usage* over the next 12 months, where $s_t \in \mathbb{R}_0^+$ and $p_t \in \mathbb{R}_0^+$ are the monthly spending and repayment amounts in month $t \in \{1, ..., 12\}$, respectively. We assume that there is no uncertainty in u.

Let $c = \langle f, r\rangle$ be a *credit card* with two features: an annual fee $f \in \mathbb{R}_0^+$ (quoted as an upfront cost) and an annual interest rate $r \in \mathbb{R}_0^+$, quoted as a percentage per annum. We assume that each credit card has a billing cycle and an interest-free period of one calendar month, and that all other card features are held constant.

In this model, the only benefit of using a credit card is the opportunity to access interest-free credit each month. We calculate the *total monetary benefit* of this opportunity following the approach outlined by Doyle (2018):

$$\alpha(u) = \frac{r_{alt}}{12} \sum_{t=1}^{12} s_t, \tag{1}$$

where $r_{alt} \in \mathbb{R}_0^+$ reflects the consumer's alternative borrowing rate[1] per annum and s_t is the monthly spending amount as defined in u. For a given consumer, the value of interest-free borrowing is the same across all cards since it does not depend on the cards' interest rate.

The *total borrowing cost* of using a credit card is the sum of its annual fee and total interest charges over the next 12 months. The former is fixed, while the latter depends on the card's interest rate and the consumer's card usage, which we define below.

To calculate *interest charges*, we assume monthly compounding to match the frequency of spending[2] in u and use the terminology commonly used in credit card statements.

Let $\mathbf{O}_{c,t} \in \mathbb{R}_0^+$ be the opening balance of a credit card c in month t, which is equivalent to the amount owing at the end of the previous month after repayment. If the opening balance is positive (i.e., owing), the consumer loses his or her interest-free status that month, and interest $\mathbf{I}_{c,t} \in \mathbb{R}_0^+$ is charged at the end of the month on $\mathbf{O}_{c,t}$ and any new purchases made during that month. Monthly interest is calculated based on the card's monthly interest rate, $r/12$.

We then define the closing balance, $\mathbf{B}_{c,t} \in \mathbb{R}_0^+$, as the sum of the opening balance, total new purchases, and interest charges at the end of the month *before* repayment. For repayment, we assume that the consumer always make at least the minimum repayment required by the card provider to avoid any late payment fees. A standard industry practice is to set the minimum repayment as the maximum of either a prespecified amount ($\$x$) or a proportion of the monthly closing balance ($y\% \cdot \mathbf{B}_{c,t}$), with the amount being no greater than $\mathbf{B}_{c,t}$.

We assume that the first month is always interest-free since the opening balance is zero ($\mathbf{O}_{c,1} = 0$) and no balance is transferred to the card. In subsequent months, interest accrues when $\mathbf{O}_{c,t} > 0$, which needs to be calculated iteratively. To calculate a card's monthly opening balance, interest charges, and closing balance, we use the following set of equations:

$$\begin{aligned} \mathbf{O}_{c,t} &= \mathbf{B}_{c,t-1} - p_{t-1} && \textbf{if } t > 1\textbf{, else } 0 \\ \mathbf{I}_{c,t} &= \frac{r}{12}(\mathbf{O}_{c,t} + s_t) && \textbf{if } \mathbf{O}_{c,t} > 0\textbf{, else } 0 \\ \mathbf{B}_{c,t} &= \mathbf{O}_{c,t} + s_t + \mathbf{I}_{c,t}, \end{aligned} \tag{2}$$

[1]For example, the interest rate of a personal loan. For consumer who would otherwise not borrow, r_{alt} can reflect the opportunity cost of borrowing, such as the savings rate.

[2]This assumption can be modified to reflect daily compounding by listing purchases in u on a daily basis.

where $\mathbf{B}_{c,t} \geq p_t \geq \min(\mathbf{B}_{c,t},\ \max[\$x, y\% \cdot \mathbf{B}_{c,t}])$.

For a consumer with card usage u, the *value* of a credit card, $\mathcal{V}(u, c)$, is defined as total monetary benefit minus total borrowing cost over 12 months:

$$\mathcal{V}(u, c) = \alpha(u) - (f + \sum_{t \in \{1,\ldots,12\}} \mathbf{I}_{c,t}). \tag{3}$$

Because the monetary benefit of interest-free borrowing is the same across all cards for a consumer, we can simplify Equation 3 to:

$$\mathcal{V}(u, c) \propto -(f + \sum_{t \in \{1,\ldots,12\}} \mathbf{I}_{c,t}). \tag{4}$$

Finally, suppose there are n credit cards available in the market, $\mathcal{C} = \{c_1, \ldots, c_n\}$. The *optimal credit card*, c^*, for a consumer with card usage u is the one that minimizes total borrowing cost over 12 months:

$$c^* = \arg\max_{c_i \in \mathcal{C}} \mathcal{V}(u, c_i). \tag{5}$$

B. *Quantifying complexity*

We present a formal framework for measuring the complexity of consumer problems by quantifying the computational resources required to solve them. Let $M(n)$ denote a consumer problem with $n \in \mathbb{N}$ number of inputs, and let its computational complexity, $\Phi(M(n))$ represent the time or memory needed to compute the optimal solution. In this paper, we operationalize complexity as the number of elementary computations, such as additions and subtractions, required to select the optimal credit card (defined in Section I.A), assuming negligible and constant search and parsing costs. In our setting, complexity arises from two sources: (1) the composition of card features in the choice set, and (2) the number of balance-carrying periods in the consumer's card usage over 12 months.

We start by categorizing credit cards into three types based on their feature composition. Let c be a credit card of one of the following types: (i) *fee-only* cards, $F = \{c | c = \langle f, 0\rangle, c \in \mathcal{C}\}$; (ii) *rate-only* cards, $R = \{c | c = \langle 0, r\rangle, c \in \mathcal{C}\}$; and (iii) *fee-rate* cards, $B = \{c | c = \langle f, r\rangle, c \in \mathcal{C}\}$.

We then re-define a consumer's card usage based on the number of months in which the opening balance is positive. Let $t(k)$ denote a consumer's card usage over 12 months, where $k = \{0, 1, \ldots, 11\}$ is the number of balance-carrying months (up to 11, since the first month is always interest-free in our model). Consumers who always make full repayments ($k = 0$) are classified as *transactors*, while those who carry a balance from month to month $k > 0$ are *revolvers*. Although *revolvers* pay interest only on rate-bearing cards, we refer to balance-carrying months as *interest compounding periods* for ease of exposition.

Based on our framework, calculating monthly interest charges involves six elementary computations: one subtraction, three additions, one division, and one multiplication (see Equation 2). Summing interest charges over k interest compounding periods involves $k - 1$ operations. Finally, adding the annual fee requires an additional computation. The total number of elementary computations involved in valuing a card, $\Phi(t(k), c) \in \mathbb{N}$, is thus:

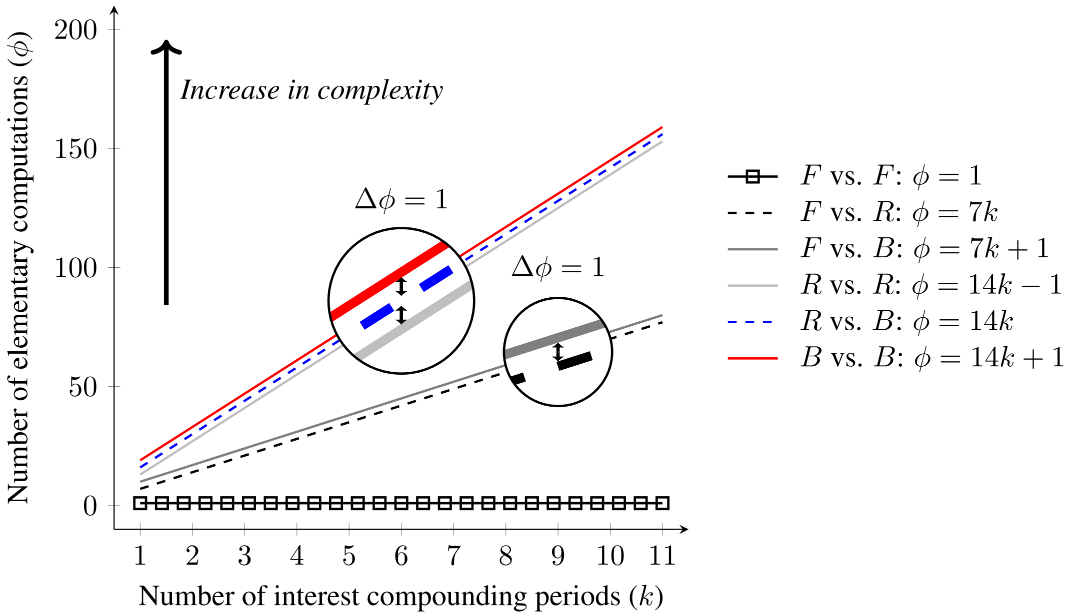
$$\Phi(t(k), c) = \begin{cases} 0 & \text{if } c \in F, \\ \max(0, 7k - 1) & \text{if } c \in R, \\ 7k & \text{if } c \in B. \end{cases} \tag{6}$$

For *fee-only* cards, $c \in F$, we assume zero computations, as their value is simply the annual fee, and the costs of searching and parsing card information are negligible and constant. When $k = 0$, the consumer is a *transactor* and never incurs interest charges, so no computations are required for any card. We next quantify the complexity of binary credit card choices.

Let $d = (c_i, c_j) \in \mathcal{C}^2$ denote a binary decision between two cards. To calculate the computational complexity of a binary credit card decision, we use Equation 6 to determine the number of elementary computations required to value each card, plus an additional step to compare the two options. We denote $\phi(t(k), d) \in \mathbb{N}$ as the computational complexity of a binary decision d between cards i and j by a consumer $t(k)$, as follows:

$$\phi(t(k), d) = \Phi(t(k), c_i) + \Phi(t(k), c_j) + 1 \tag{7}$$

With only two features per option and no uncertainty in card usage, this decision problem is deterministic. Importantly, our framework shows that *revolvers* always face a credit card decision that is *weakly* more computationally complex than that faced by *transactors*. This is the case because *transactors* use credit cards solely for convenience, and therefore the only



Note: This figure illustrates how the number of elementary computations involved in making a credit card decision (ϕ) increases with the number of interest compounding periods, k, for all decisions, except *fee-only* versus *fee-only* cards. F, R, and B denote *fee-only*, *rate-only*, and *fee-rate* cards, respectively. $\Delta\phi$ represents the difference in the number of elementary computations between two decision types. For example, $\Delta\phi$ between *fee-rate* versus *fee-rate* and *rate-only* versus *fee-rate* decisions is one unit, so is the case between *rate-only* versus *fee-rate* and *rate-only* versus *rate-only* decisions.

FIGURE 1. COMPLEXITY OF CREDIT CARD DECISIONS FACED BY A REVOLVER.

relevant feature when comparing options is the annual fee. Consequently, it only requires one elementary computation to choose the optimal card, regardless of the card type (see Equations 6 and 7, where $k = 0$).

For *revolvers*, on the other hand, the computational complexity of credit card decisions depends on both their card usage and the options' card type (see Figure 1). First, the number of elementary computations increases linearly with k for all decisions, except when both options are *fee-only*, in which case the decision reduces to that faced by *transactors*. Second, and more importantly, the growth rate is determined by the number of rate-bearing options in the decision: complexity grows the fastest when both options are rate-bearing, with the most complex decisions involving two *fee-rate* cards, while decisions with only one rate-bearing option increases at only half the rate.

Our framework thus demonstrates that the computational complexity of credit card decisions is driven by two key factors: (1) the number of rate-bearing options in the choice set and (2) the number of interest compounding periods in a consumer's card usage pattern. Importantly, the first factor is relevant only for *revolvers*.

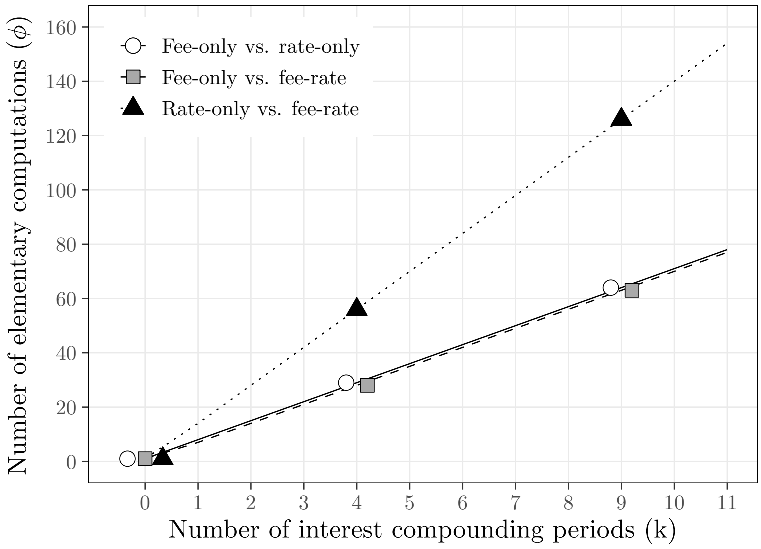
II. Experimental design

We design a combined behavioral and eye-tracking experiment to examine how the complexity of binary credit card decisions affects financial decision-making. Complexity is operationalized along the two dimensions outlined in our framework in Section I.B: (1) the composition of card features in a decision (hereinafter, *decision type*), and (2) the number of interest compounding periods in card usage over 12 months. In addition, we vary two secondary features of credit card choices to account for decision errors caused by noisy information processing but are not modelled in our framework: (3) the presentation of digits in monthly card usage, and (4) the similarity of option values. Based on these four parameters, we generated 41 binary credit card decisions using card features parameterized from the Australian market. All amounts are expressed in Australian dollars. The details of each parameter are described below.

Decision type.— We construct three decision types from the three card categories defined in Section I.B: (i) *fee-only* versus *rate-only*, (ii) *fee-only* versus *fee-rate*, and (iii) *rate-only* versus *fee-rate*, listed in ascending order of complexity. According to our framework, *fee-only* versus *fee-rate* decisions are only marginally more computationally demanding than *fee-only* versus *rate-only* decisions, as the former requires one additional step to add the annual fee when valuing the rate-bearing option. These binary choices approximate decisions among credit card products offered by the same issuer.

Card usage.— We manipulate the number of interest compounding periods by varying the timing of the minimum repayment within a 12-month period to generate *transactor* and *revolver* trials. A *transactor* trial involves full repayment each month, resulting in zero interest compounding. On the other hand, a *revolver* trial introduces a minimum repayment in one of the 12 months, while repayments in all other months equal monthly purchases. The unpaid balance is then carried forward, accruing interest in subsequent months. Specifically, the timing of the minimum repayment occurs either in the third month (“hard”, nine compounding periods) or the eighth month (“easy”, four compounding periods). All else equal, *transactor* trials are the simplest, while *revolver-hard* trials are the most complex.

Figure 2 illustrates the number of elementary computations involved across the two complexity dimensions. The most computationally demanding decisions are *revolver-hard* trials comparing *rate-only* and *fee-rate* cards, while the least demanding are *transactor* trials, regardless of decision type.



Note: Each point represents a binary credit card decision in the experiment, varying by decision type and the number of interest compounding periods (k). The costs of searching and parsing feature information are assumed to be negligible and constant across all decisions.

FIGURE 2. NUMBER OF ELEMENTARY COMPUTATIONS INVOLVED (ϕ) IN MAKING A CREDIT CARD DECISION.

Because interest compounding involves non-trivial computation and human information processing is inherently noisy, we introduce two additional parameters to account for decision noise not modeled in our framework. Specifically, we vary the presentation of digits and the value similarity between options. These complexity moderators apply only to *revolver* trials, as *transactor* trials involve no interest calculations.

Presentation of digits.— In each *revolver* trial, monthly spending is fixed at either \$1,000, \$1,500, or \$1,800.[3] While parsing digits is computationally trivial relative to interest calculation, individuals may perceive certain digit sequences as more cognitively demanding. For example, \$1,000 may appear easier to process than \$1,800, even when this difference has minimal computational consequence. Digit presentation may also induce behavioral anomalies such as left-hand digit bias, in which individuals focus on the leftmost digits of a number to reduce cognitive load, leading to valuation errors (Thomas and Morwitz, 2009).

Value similarity.— We vary value similarity across *revolver* trials. Prior research shows that consumers are more likely to choose the optimal credit card when financial stakes higher (Agar-

[3] At the time of writing, credit limits on Australian *fee-only* cards ranged from A\$1,000 to A\$3,000 per month. Total credit card debt on personal cards was A\$32.6 billion, with 55% of this debt accruing interest (Reserve Bank of Australia, 2025). The average balance per account was A\$2,800 and the average repayment was A\$2,500. Assuming 30-40% of accounts accrue interest (Reserve Bank of Australia, 2015), the average balance accruing interest was estimated to range from A\$3,900 to A\$5,200, compared to A\$1,800 to A\$2,100 for accounts not accruing interest.

wal et al., 2015). This may reflect that higher stakes increase the salience of mistake costs or, alternatively, that larger value differences make the optimal option easier to identify by requiring less precise valuation. Because consumers process information noisily and often make valuation errors, accounting for value similarity is particularly important in binary choices involving feature trade-offs, such as when one card offers a lower annual fee but a higher interest rate. In this study, trials are classified as having *high* value similarity when the value difference is $20 or less, and *low* when it exceeds $20.[4]

Sampling.— To reflect real-world choices, we sampled credit card offerings from the Australian market[5], which is broadly comparable to other Western markets, such as the United States and the United Kingdom, in terms of product features and market competitiveness. At the time of sampling, 285 credit cards were available. Since our focus is on cards with only an annual fee and interest rate, we excluded those offering rewards, cashback, and frequent flyer points, as well as business or corporate cards, and credit union cards. This yields a sample of 81 cards. We then grouped these cards into the three card types defined in I.B, and further excluded 20 cards whose features did not fit these categories. We assume that all other features, such as credit limits and balance transfer rates, are equivalent across cards and that no eligibility restrictions apply. The final sample consisted of 61 cards categorized into the three card types defined in Section I.

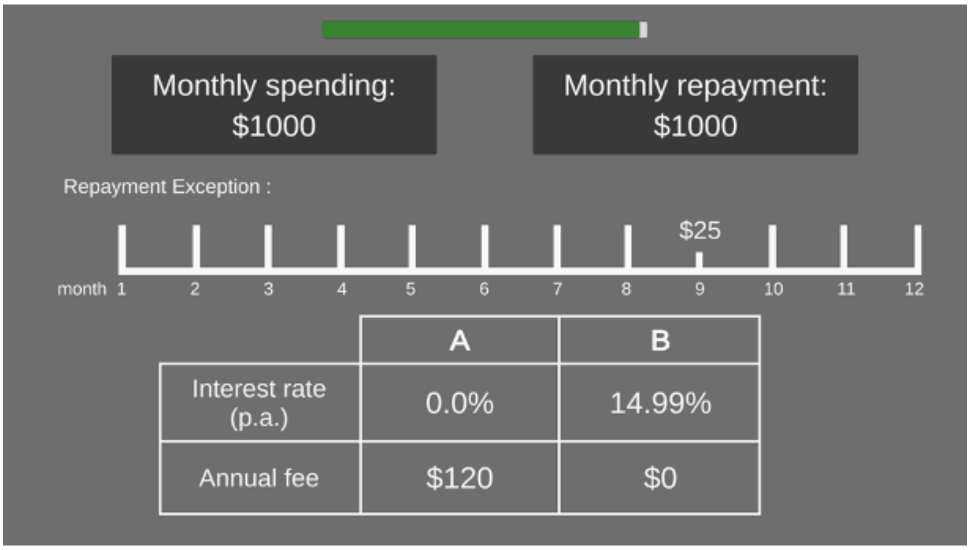
Using these 61 cards, we simulated borrowing costs under varying interest compounding periods (see Supplemental Appendix A). The results show that many cards cluster around similar borrowing costs, which may be difficult for consumers, particularly *revolvers*, to identify the optimal option.

Final Sample.— We used the 61 sampled cards and four experimental parameters to construct 41 binary credit card decisions. First, we randomly generated a *revolver* trial for each of the 36 parameter combinations, except for three infeasible cases: *revolver-hard* trials comparing *rate-only* and *fee-only* cards with high value similarity across all monthly spending levels.[6] We replaced the decision type of these missing combinations with *rate-only* versus *fee-rate* decisions, as they are more common in the market but underrepresented at higher levels of complexity in this study (see Figure 2). The final 36 *revolver* trials were constructed from 26

[4]This cut-off was determined through pilot testing, which found that participants easily discriminated between options when the value difference exceeded $50.

[5]We sampled from the comparison site, Finder.com.

[6]*Fee-only* cards were always more than $20 above the *rate-only* options.



Note: This screenshot shows a *revolver* trial with monthly purchases of $1,000, a minimum repayment of $25 occurring in month nine, and two options: a *fee-only* and a *rate-only* card.

FIGURE 3. A SCREENSHOT OF A TRIAL SCREEN IN THE CHOICE TASK.

unique Australian credit cards.

The same set of cards was used to create six random *transactor* trials, two for each decision type. All *transactor* trials have low value similarity, as they involve no interest calculations and fee differences always exceeded $20.

We observe a clear trade-off between annual fees and interest rates across the three card types ($\beta = -0.1$, $s.e. = 0.02$, $p < 0.05$)[7], indicating that no single card type dominates for *revolvers* without accounting for his or her card usage.

A. *Procedure*

The experiment was in person and consisted of a choice task followed by a questionnaire. Participants began with general instructions about the experiment, including information explaining how a typical credit card works. They then completed five comprehension questions and five practice trials to ensure understanding of the choice task. A copy of the full instructions is available in Supplemental Appendix B.

The choice task[8] consisted of 41 randomly ordered trials. Each trial involved a binary decision presented across three sequential screens: a trial screen, a choice screen, and a rating screen. The trial screen showed two card options and a hypothetical card usage, which included information about fixed monthly spending and repayment over 12 months, along with a timeline

[7]Clustered standard errors were used in the linear regression analysis
[8]Programmed in Unity3D.

stating the timing and amount of the minimum repayment[9]. The two card options and their respective features were presented in a table below the timeline. Figure 3 shows a trial screen involving a *revolver* trial with monthly purchases of $1,000, a minimum repayment of $25 occurring in month nine, and two options: a *fee-only* and *rate-only* card. Participants then proceeded to the choice screen to select an option, followed by the rating screen where they evaluated the trial's difficulty on a five-point Likert scale (1 = "very easy", 5 = "very hard").

Participants were given 60 seconds on the trial screen, 5 seconds on the choice screen, and unlimited time on the rating screen. They could proceed to the choice screen at any time before the 60-second limit.

After completing the choice task, participants filled out a questionnaire measuring demographics, real-life credit card usage, financial, debt, and risk literacy, and numeracy (see Supplemental Appendix C for the full questionnaire).

Eye tracking.— Eye movements were recorded using a screen-based eye-tracker (Tobii Pro Spectrum). Areas of interest (AOIs) were pre-defined on the trial screen based on the three visually observable parameters: (a) card features, (b) the timing and amount of the minimum repayment, and (c) the number of digits in monthly spending and repayment (see Supplemental Appendix D.D1 for the eye-tracking setup).

Incentivization.— Participants received a fixed participation fee of A$15 for completing the experiment plus a bonus reward of up to A$25, depending on their performance in the choice task. The maximum possible payout was A$40. All payments were made in Australian dollars. The experimental protocol was approved by the University of Melbourne Human Research Ethics Committee (Ethics ID 25383) and conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent before participating in the study.

B. Data Analysis

In this section, we summarize the estimation strategy used to analyze the empirical data. We first estimate the impact of decision complexity on choice quality, cognitive effort, information acquisition, and perceived difficulty, and then examine how these behavioral outcomes relate to individual sophistication, measured by financial, debt, and risk literacy, and numeracy. Full details are reported in Supplemental Appendix E.

[9]The minimum repayment is the maximum of either 2% of the monthly spending amount or $25, which is the typical requirement in Australia.

To examine the effect of complexity on credit card decision-making, we analyze participants' choice quality, cognitive effort, information acquisition, and subjective difficulty during the choice task.

Choice quality is measured either as a binary indicator of a correct response in each trial or the proportion of correct responses across all trials. Cognitive effort is proxied by the amount of time a participant spends on the trial screen, with longer response times assumed to reflect higher cognitive effort. Information acquisition is captured by the total number of fixations on the AOIs per trial, where a fixation refers to an event in which a participant looks at an AOI for at least 60 ms. Since fixations represent deliberate control of information search (Kahneman, 1973), higher fixation counts indicate greater information acquisition effort. Prior work has shown that both response time and fixation counts increase with task difficulty (Krajbich, Armel and Rangel, 2010). To examine how participants acquire feature information, we also calculate the *fixation gap* between interest rates and annual fees of both options. A positive difference indicates more fixations on interest rates. Lastly, subjective difficulty is measured using participants' self-reported difficulty ratings on a five-point Likert scale, where 1 indicates "very easy" and 5 "very hard".

We conduct two sets of analyses using mixed-effects models with random intercepts for participants and decisions to account for within-subject and within-choice variations in the behavioral measures. For the eye-tracking measures, we include only participant-level random effects due to missing observations at the decision-level (see Supplemental Appendix D.D2 for eye-tracking data quality). First, we estimate the total effect of complexity on credit card decision-making by using the number of elementary computations involved in choosing credit cards (ϕ) as the main independent variable. This measure captures the overall *hardness* of credit card decisions from varying the two complexity parameters: decision type and number of interest compounding periods. Second, we examine the relative contribution of each complexity parameter by including them as separate independent variables. The two complexity moderators, presentation of digits and value similarity of options, are included as covariates in all specifications. Model selection is based on the Akaike Information Criterion (AIC).

To explore the role of individual sophistication, measured by financial, debt, and risk literacy, and numeracy, in credit card decision-making, we estimate ordinary least squares regressions of aggregate behavioral outcomes on literacy scores. Specifically, we regress average choice quality, cognitive effort, and subjective difficulty on the four literacy measures, controlling for age and current or past credit card ownership (binary indicators).

III. Results

We recruited 26 participants from the University of Melbourne community. One participant was excluded from the analysis for failing to attend to the task. Our final dataset consists of 25 participants, 1,025 behavioral observations, and 823 fixation observations across 41 binary choices. The quality of the eye-tracking data is reported in Supplemental Appendix D.D2.

The mean age of our sample was 24.16 years (range = 18-35 years), with 32% reported owning at least one credit card and 12% reported having previously owned one at the time of the experiment. Among those who currently own credit cards, the average number of cards held was 2.25. Participants performed well on financial literacy (85.33%, standard deviation [s.d.] = 21.69%) and numeracy (93.6%, s.d. = 14.11%) tests, but lower on risk literacy (54%, s.d. = 32.02%) and debt literacy (52%, s.d. = 25.6%) assessments. All test scores are higher than those reported in the literature (detailed descriptive statistics are provided in Supplemental Appendix F.F1).

In the choice task, mean performance was 66.24% (s.d. = 10%), below the benchmark of 68.29%, which is based on a simple heuristic of always choosing the lower-fee option in *transactor* trials and the lower-rate option in *revolver* trials. Only nine participants (36%) outperformed this benchmark. On average, participants spent 33.06 seconds (s.d. = 9.22s) per trial and made 49.62 fixations (s.d. = 20.54). The average fixation gap between interest rates and annual fees was 10.53 (s.d. = 5.56). The average subjective difficulty rating was 2.89 (s.d. = 0.32) per trial. Full summary statistics for the choice task are reported in Supplemental Appendix F.F2.

Figure 4 presents the average behavioral and eye-tracking results across varying levels of decision complexity. Panel A shows the overall effect of complexity, measured by the number of elementary computations involved in choosing the optimal card (ϕ). Panel B decomposes this effect along the two complexity dimensions: (1) the decision type and (2) the number of interest compounding periods in card usage.

As expected, choice quality decreased with increasing complexity, while cognitive effort, fixation activities, and subjective difficulty all increased. In *transactor* trials, all participants correctly chose the lower-fee option, while in *revolver* trials, mean task performance was 60.46% (s.d. = 11.71%) compared to the benchmark of 62.86%, although this difference was not statistically significant at the 5% level. These mistakes correspond to an average monetary loss of \$46.10 per choice (s.d. = \$16.96) and a cumulative loss of \$675.74 (s.d. = \$370.03) per participant across all trials.

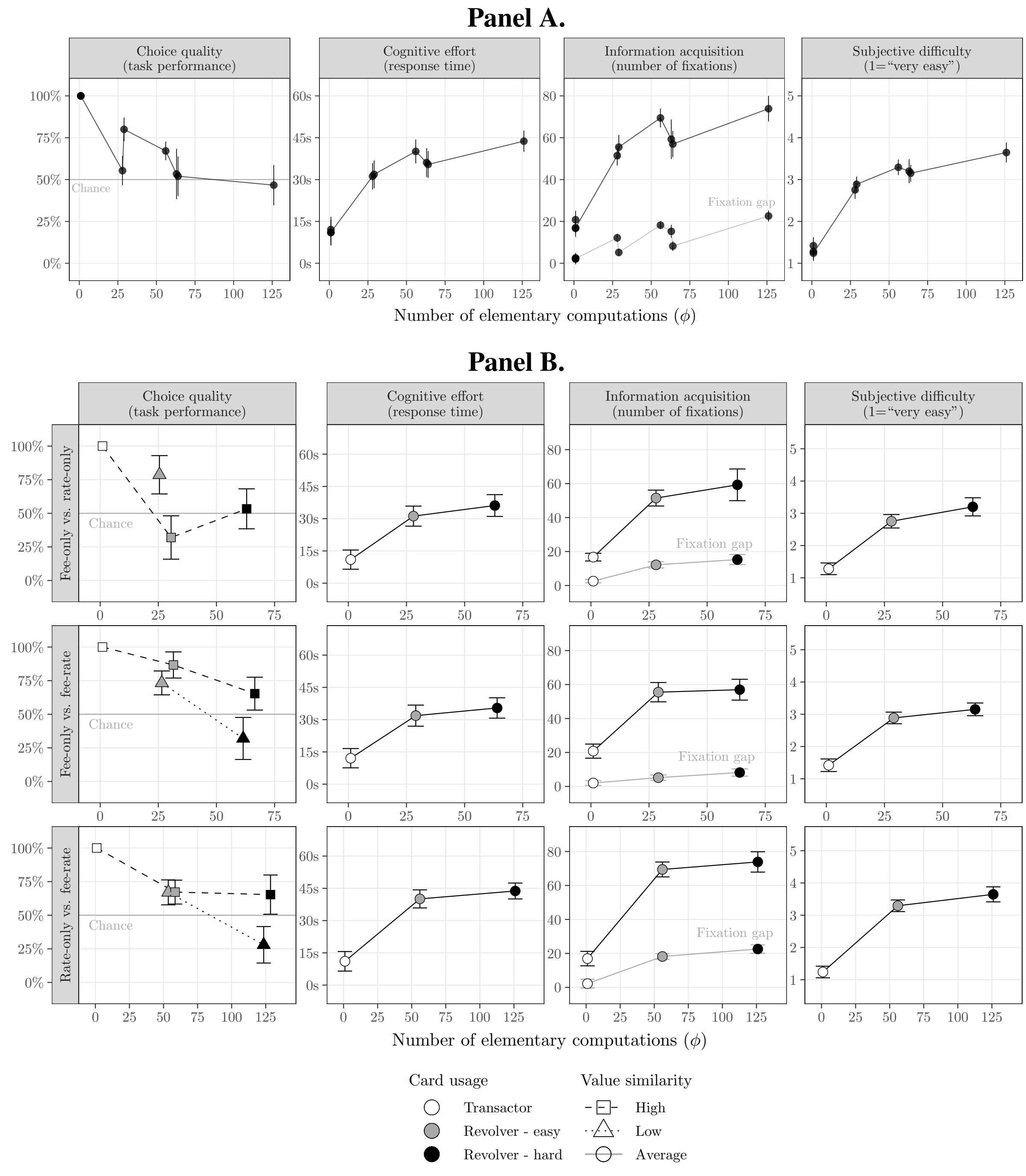
Compared to *revolver* trials, participants spent and made roughly 30% as much time and fixations in *transactor* trials, which they also rated as the easiest. The average fixation gap between interest rates and annual fees was near zero (mean = 2.25, s.d. = 3.42) in *transactor* trials but increased to 13.17 (s.d. = 5.11) in *revolver* trials.

A. *Choice quality*

Table 1 reports the main results for choice quality. Consistent with our framework, greater computational complexity significantly reduced the likelihood of choosing the optimal credit card (column 1, coefficient estimate [coeff] = -1.27, standard error [s.e.] = 0.26, $p < 0.001$). Importantly, this likelihood fell below chance (50%) once a binary decision required more than 86 elementary computations, which is equivalent to a consumer choosing between two rate-bearing options with the expectation of missing full repayments for more than six months. In the most complex decisions in our study (126 elementary computations), where the optimal choice was always the lower-rate card, mean choice quality fell to 46.67%.

Including the complexity moderators, presentation of digits and value similarity, did not change this result (column 2), largely because these moderators had no effect in *transactor* trials, where all participants chose optimally. Restricting the analysis to *revolver* trials provides additional insights (columns 3-6).

When *transactor* trials are excluded, the effect of complexity on choice quality becomes insignificant in the absence of the complexity moderators (column 3, coeff = -0.75, s.e. = 0.39, $p > 0.05$). However, once the moderators are included (column 4), value similarity significantly moderates the impact of complexity on choices quality. In the simplest *revolver* trials comparing *fee-only* and *rate-only* cards, participants were more likely to err when value similarity was low (coeff = -7.50, s.e. = 1.95, $p < 0.001$). As computational demands increased, this relationship was reversed, as shown by the positive interaction term (coeff = 1.83, s.e. = 0.67, $p < 0.01$). Importantly, at higher levels of complexity, participants only performed worse when options were similar in value. In the most complex decisions, the predicted probabili-



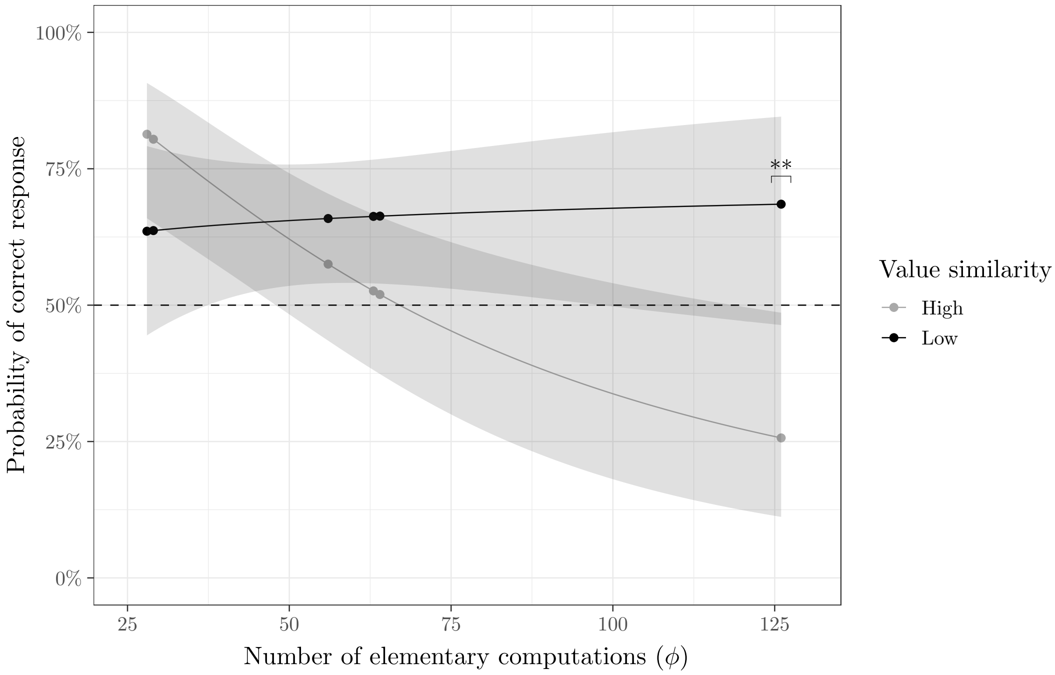
Note: This figure reports behavioral and eye-tracking measures from the choice task: choice quality, measured by the proportion of correct choices; cognitive effort, measured by response time; information acquisition, measured by the number of fixations and the fixation gap between rates and fees; and subjective difficulty, measured on a five-point Likert scale from 1 ("very easy") to 5 ("very hard"). Panel A plots average outcomes by total decision complexity, measured by the number of elementary computations involved in making a binary credit card decision (ϕ). Panel B presents averages by decision type and card usage, aggregated across monthly spending levels and value similarity, except for choice quality (first column), which is further grouped by value similarity. Error bars indicate 95% confidence intervals.

FIGURE 4. BEHAVIORAL AND EYE-TRACKING RESULTS IN THE CHOICE TASK.

TABLE 1—EFFECTS OF COMPLEXITY ON CHOICE QUALITY

	Total effect				Decomposed effects	
	All trials		*Revolver* trials		*Revolver* trials	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	5.65	7.53	3.55	7.50	0.28	1.87
	(1.02)	(2.16)	(1.58)	(1.95)	(0.46)	(0.50)
Total complexity (log of ϕ)	−1.27	−1.70	−0.75	−1.69		
	(0.26)	(0.54)	(0.39)	(0.48)		
Revolver-hard					−0.10	−0.69
					(0.78)	(1.01)
Fee-only vs. fee-rate					1.41	−0.15
					(0.65)	(0.65)
Rate-only vs. fee-rate					0.63	−0.60
					(0.58)	(0.59)
Revolver-hard × Fee-only vs. fee-rate					−1.47	−1.45
					(1.03)	(1.24)
Revolver-hard × Rate-only vs. fee-rate					−0.97	−1.17
					(0.97)	(0.83)
Monthly spending = $1,500		−0.86		−0.90		−0.91
		(0.46)		(0.42)		(0.32)
Monthly spending = $1,800		−0.30		−0.34		−0.46
		(0.47)		(0.43)		(0.33)
Low similarity		−1.91		−7.02		−2.24
		(2.34)		(2.69)		(0.63)
Total complexity × Low similarity		0.57		1.83		
		(0.59)		(0.67)		
Revolver-hard × Low similarity						1.69
						(0.81)
Fee-only vs. fee-rate × Low similarity						3.03
						(0.92)
Rate-only vs. fee-rate × Low similarity						2.30
						(0.82)
Revolver-hard × Fee-only vs. fee-rate × Low similarity						−0.83
						(1.26)
Participants	25	25	25	25	25	25
Observations	1,025	1,025	875	875	875	875
AIC	1,035.09	1,038.26	1,031.64	1,028.99	1,033.56	1,023.08

Note: This table reports coefficient estimates from logistic mixed effects models for choice quality in the choice task, using all trials in columns 1-2 and *revolver* trials only in columns 3-6. The dependent variable is the probability of choosing the optimal credit card. In columns 1-4, the main independent variable is the log of the number of elementary computations involved in choosing the optimal card in a binary choice (ϕ), which captures total decision complexity. Columns 5-6 decompose this effect into the two complexity parameters: decision type and card usage. For decision type, the dummy variables correspond to the more computationally demanding decision pairs: *fee-only* versus *fee-rate* cards and *rate-only* versus *fee-rate* cards, with *fee-only* versus *rate-only* cards as the reference. For card usage, the dummy variable corresponds to *revolver-hard* trials, with *transactor* trials as the reference. A positive coefficient indicates a higher probability of choosing the correct option. Columns 1, 3, and 5 include only complexity measures. Columns 2, 4, and 6 additionally control for the two complexity moderators: digit presentation and value similarity, and the latter's interaction with complexity. For digit presentation, the dummy variables correspond to higher monthly spending levels: $1,500 and $1,800, with $1,000 as the reference. For value similarity, the dummy variable equals one for low value similarity. Interaction terms that could not be estimated due to infeasible parameter combinations (see Section II) are omitted. Estimates are reported as log-odds ratios. Standard errors are clustered at the participant and choice level, and shown in parentheses.



Note: This figure reports the contrast between high and low value similarity *revolver* trials on the predicted probability of choosing the optimal credit card option across increasing levels of elementary computations, averaged over monthly spending. Estimates are based on column (4) from Table 1. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

FIGURE 5. TOTAL EFFECT OF COMPLEXITY ON CHOICE QUALITY IN REVOLVER TRIALS WITH 95% CIS.

ties of making a mistake was 42.85% higher in high value similarity trials than in low value similarity trials (95% confidence intervals [CI] = [15.74%, 69.95%], $p < 0.01$; see Figure 5).

Additionally, participants were more likely to make a mistake when monthly spending was $1,500 (coeff = -0.90, s.e. = 0.42, $p < 0.05$) compared to the reference amount of $1,000, but not when it was $1,800 (coeff = -0.34, s.e. = 0.43, $p > 0.05$). This may reflect rounding behavior, where rounding $1,800 to $2,000 is likely to preserve choice consistency, while rounding $1,500 up or down introduces greater valuation noise.

Columns 5-6 decompose total credit card decision complexity into the two complexity parameters: (1) decision type and (2) card usage. Results show that card usage, as measured by the number of interest compounding periods, has a larger negative effect on choice quality than decision type, although the main effects are relatively weak and mostly insignificant. On the other hand, their interactions with low value similarity were mostly positive and statistically significant at the 5% level. This reinforces that complexity impairs choice quality only when options are difficult to distinguish.

TABLE 2—TOTAL EFFECT OF COMPLEXITY ON COGNITIVE EFFORT AND INFORMATION ACQUISITION

	Cognitive effort		Information acquisition			
	Log of response time		Number of fixations		Fixation gap between rates and fees	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.10	2.43	17.27	14.62	0.40	0.32
	(0.07)	(0.23)	(3.76)	(4.06)	(1.18)	(1.36)
Total complexity (log of ϕ)	0.34	0.25	10.89	11.09	3.42	3.44
	(0.01)	(0.06)	(0.56)	(0.57)	(0.24)	(0.25)
Monthly spending = $1,500		0.01		1.00		−0.62
		(0.05)		(2.09)		(0.91)
Monthly spending = $1,800		0.06		4.80		0.61
		(0.05)		(2.09)		(0.92)
Low similarity		−0.38				
		(0.22)				
Total complexity × Low similarity		0.09				
		(0.06)				
Participants	24	24	25	25	25	25
Observations	984	984	823	823	823	823
AIC	1,530.23	1,549.73	7637.35	7629.05	6255.12	6254.19

Note: This table reports coefficient estimates from linear mixed effects models for cognitive effort and information acquisition. The dependent variables are the log of total seconds spent on the trial screen in columns 1-2, the number of fixations in columns 3-4, and fixation gap between rates and fees in columns 5-6. The main independent variable is the log of the number of elementary computations involved in choosing the optimal card in a binary choice (ϕ), which captures total decision complexity. A positive coefficient indicates longer decision time in columns 1-2 and great effort to acquire information in columns 3-6. Each observation corresponds to a participant-choice. Columns 1, 3, and 5 report the results using only the complexity metric. Column 2 includes the complexity moderators: digit presentation and value similarity, and the latter's interaction with complexity. For digit presentation, the two dummy variables correspond to higher monthly spending levels ($1,5000 and $1,800), with $1,000 as the omitted level. For value similarity, the dummy variable is for low value similarity. Column 3 and 5 include only digit presentation dummy variables as value similarity is not visually presented in the choice task. Estimates are reported as log-log coefficients in columns 1-2 and level-log coefficients in columns 3-6. Standard errors are clustered at the participant and choice level, and shown in parentheses.

B. *Cognitive effort and information acquisition*

We next examine how decision complexity affects cognitive effort and information acquisition. Cognitive effort is proxied by response time on the trial screen, while information acquisition is measured by the total number of fixations and the fixation gap between interest rates and annual fees.

Out of 1,025 trials, 160 exceeded the 60-second time limit (15.61%), with the proportion of timed-out trials increasing with computational demands: 0.59% in *transactor* trials, 7.41% in *revolver-easy* trials, and 7.61% in *revolver-hard* trials. Notably, all timed-out *transactor* trials came from a single participant, who exceeded the time limit on every trial while scoring 75.61% overall. This participant was excluded from the response time analysis.

Table 2 presents the main effects of total decision complexity. As expected, participants exerted greater effort and made more fixations as computational demands increased. A 10% increase in ϕ led to a 3.4% increase in response time (column 1, s.e. = 0.01, $p < 0.001$) and one additional fixation (column 3, coeff = 10.89, s.e. = 0.56, $p < 0.001$). While cognitive effort was driven solely by computational demands (column 2), fixation activity was also affected by digit presentation (column 4): Participants made more fixations when monthly spending was $1,800 (coeff = 4.80, s.e. = 2.09, $p < 0.05$).

Although participants worked harder, their performance still declined with complexity, suggesting suboptimal information acquisition. To examine this, we measured the fixation gap and found that participants fixated more on the complexity-relevant feature, that is, interest rates, as the number of interest computations increased (column 6, coeff = 3.44, s.e. = 0.25, $p < 0.001$).

Table 3 decomposes these effects by decision type and card usage. Card usage, operationalized by the number of interest compounding periods, was the primary driver of cognitive effort and information acquisition. Compared to *transactor* trials, participants spent 120% more time in *revolver-easy* trials (column 1, s.e. = 0.08, $p < 0.001$) and 136% more time in *revolver-hard* trials (s.e. = 0.09, $p < 0.001$). They also made 34.05 more fixations in *revolver-easy* trials (column 4, s.e. = 3.74, $p < 0.001$) and 42.66 in *revolver-hard* trials (s.e. = 4.29, $p < 0.001$). Additionally, fixation gap widened with the number of interest compounding periods: 9.16 in *revolver-easy* trials (column 6, s.e. = 1.50, $p < 0.001$) and 12.51 in *revolver-hard* trials (s.e. = 1.72, $p < 0.001$). Finally, fixation measures, particularly the fixation gap, were also influenced by decision type in *revolver* trials, suggesting that participants selectively attended to features that drive complexity.

C. Subjective difficulty

To test whether participants could detect the computational complexity of credit card choices, we asked them to rate the difficulty of each binary decision on a five-point Likert scale, where 1 indicated "very easy" and 5 "very hard". Table 4 reports the main results. Participants were more likely to rate decisions as more difficult as complexity increased (column 1, coeff = 1.34, s.e. = 0.08, $p < 0.001$). *Transactor* trials were most likely rated as "very easy", while the most complex *revolver* trials were most likely rated as "hard". Additionally, subjective difficulty varied with digit presentation but not with value similarity: Decisions with monthly spending of $1,800 were more likely to have a higher difficulty rating than those with $1,500 and $1,000 (column 2, coeff = 0.50, s.e. = 0.17, $p < 0.01$).

Similar to the cognitive effort results, subjective difficulty was primarily driven by card usage,

TABLE 3—DECOMPOSED EFFECTS OF COMPLEXITY ON COGNITIVE EFFORT AND INFORMATION ACQUISITION

	Cognitive effort		Information acquisition			
	Log of response time		Number of fixations		Fixation gap between rates and fees	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.06	2.05	16.56	13.11	2.36	2.85
	(0.08)	(0.17)	(4.31)	(4.70)	(1.41)	(1.60)
Revolver-easy	1.20	1.19	32.62	34.05	9.26	9.16
	(0.08)	(0.14)	(3.69)	(3.74)	(1.48)	(1.50)
Revolver-hard	1.36	1.38	41.15	42.66	12.58	12.51
	(0.09)	(0.09)	(4.24)	(4.29)	(1.70)	(1.72)
Fee-only vs. fee-rate	0.06	−0.03	4.36	5.55	−0.41	−0.78
	(0.10)	(0.20)	(4.61)	(4.70)	(1.85)	(1.89)
Rate-only vs. fee-rate	0.04	0.05	−0.37	1.77	−0.38	0.08
	(0.13)	(0.16)	(5.75)	(5.90)	(2.31)	(2.37)
Revolver-easy × Fee-only vs. fee-rate	−0.09	0.10	1.03	−0.11	−6.34	−5.96
	(0.12)	(0.20)	(5.55)	(5.62)	(2.23)	(2.27)
Revolver-easy × Rate-only vs. fee-rate	0.27	0.24	18.65	16.57	6.50	6.08
	(0.14)	(0.14)	(6.41)	(6.53)	(2.58)	(2.63)
Revolver-hard × Fee-only vs. fee-rate	−0.07	−0.05	−6.74	−7.43	−6.78	−6.39
	(0.13)	(0.13)	(6.02)	(6.07)	(2.42)	(2.45)
Revolver-hard × Rate-only vs. fee-rate	0.23	0.19	14.42	12.20	7.51	7.03
	(0.15)	(0.15)	(6.87)	(7.00)	(2.76)	(2.82)
Monthly spending = $1,500		0.01		1.31		−0.95
		(0.04)		(2.14)		(0.86)
Monthly spending = $1,800		0.06		4.58		−0.25
		(0.04)		(2.10)		(0.85)
Low similarity		−0.03				
		(0.14)				
Revolver-easy × Low similarity		0.02				
		(0.11)				
Fee-only vs. fee-rate × Low similarity		0.10				
		(0.17)				
Rate-only vs. fee-rate × Low similarity		0.03				
		(0.11)				
Revolver-easy × Fee-only vs. fee-rate × Low similarity		−0.31				
		(0.17)				
Participants	24	24	25	25	25	25
Observations	984	984	823	823	823	823
AIC	1,550.87	1,579.91	7589.41	7581.94	6086.36	6086.31

Note: This table reports coefficient estimates from linear mixed effects models for cognitive effort and information acquisition. The dependent variables are the log of total seconds spent on the trial screen in columns 1-2, the number of fixations in columns 3-4, and fixation gap between rates and fees in columns 5-6. The main independent variables are the two complexity parameters: decision type and card usage, which decompose the effect of total decision complexity. For decision type, the two dummy variables correspond to the more computationally demanding decision pairs: *fee-only* versus *fee-rate* cards and *rate-only* versus *fee-rate* cards, with *fee-only* versus *rate-only* cards as the reference decision type. For card usage, the dummy variable corresponds to *revolver-hard* trials, with *transactor* trials as the reference level. A positive coefficient indicates longer decision time in columns 1-2 and great effort to acquire information in columns 3-6. Each observation corresponds to a participant-choice. Columns 1, 3, and 5 report the results using only the complexity metric. Column 2 includes the complexity moderators: digit presentation and value similarity, and the latter's interaction with complexity. For digit presentation, the two dummy variables correspond to higher monthly spending levels ($1,5000 and $1,800), with $1,000 as the omitted level. For value similarity, the dummy variable is for low value similarity. Column 3 and 5 include only digit presentation dummy variables as value similarity is not visually presented in the choice task. Estimates are reported as log-level coefficients in columns 1-2 and level-level coefficients in columns 3-6. Standard errors are clustered at the participant and choice level, and shown in parentheses.

TABLE 4—EFFECTS OF COMPLEXITY ON SUBJECTIVE DIFFICULTY

	Probability of a higher difficulty rating (D)			
	(1)	(2)	(3)	(4)
Total complexity (log of ϕ)	1.34	1.18		
	(0.08)	(0.21)		
Revolver-easy			4.70	4.62
			(0.41)	(0.57)
Revolver-hard			5.68	5.87
			(0.46)	(0.42)
Fee-only vs. fee-rate			0.63	0.38
			(0.47)	(0.74)
Rate-only vs. fee-rate			−0.10	0.05
			(0.62)	(0.69)
Revolver-easy × Fee-only vs. fee-rate			−0.33	0.25
			(0.53)	(0.74)
Revolver-easy × Rate-only vs. fee-rate			1.34	1.15
			(0.67)	(0.63)
Revolver-hard × Fee-only vs. fee-rate			−0.72	−0.75
			(0.57)	(0.52)
Revolver-hard × Rate-only vs. fee-rate			1.10	0.82
			(0.70)	(0.65)
Monthly spending = $1,500		0.19		0.24
		(0.17)		(0.15)
Monthly spending = $1,800		0.50		0.52
		(0.17)		(0.15)
Low similarity		−0.83		−0.22
		(0.85)		(0.50)
Total complexity × Low similarity		0.19		
		(0.22)		
Revolver-easy × Low similarity				0.30
				(0.40)
Fee-only vs. fee-rate × Low similarity				0.41
				(0.61)
Rate-only vs. fee-rate × Low similarity				0.05
				(0.39)
Revolver-easy × Fee-only vs. fee-rate				−1.10
× Low similarity				(0.61)
Threshold coefficients (D)				
1 — 2	0.96	0.48	1.22	1.43
	(0.26)	(0.85)	(0.34)	(0.60)
2 — 3	3.99	3.54	4.30	4.51
	(0.32)	(0.83)	(0.41)	(0.64)
3 — 4	6.14	5.68	6.44	6.65
	(0.34)	(0.84)	(0.42)	(0.65)
4 — 5	8.07	7.60	8.35	8.57
	(0.37)	(0.86)	(0.44)	(0.66)
Participants	25	25	25	25
Observations	1025	1025	1025	1025
AIC	2395.08	2394.15	2401.10	2400.80

Note: This table reports coefficient estimates from cumulative link mixed effects models for subjective difficulty in the choice task, where 1 indicates "very easy" and 5 "very hard". The dependent variable is the probability of a higher difficulty rating. In columns 1-2, the main independent variable is the log of the number of elementary computations involved in choosing the optimal card in a binary choice (ϕ), which captures total decision complexity. In columns 3-4, the main independent variables are the two complexity parameters: decision type and card usage, which decompose the effect of total decision complexity. For decision type, the two dummy variables correspond to the more computationally demanding decision pairs: *fee-only* versus *fee-rate* cards and *rate-only* versus *fee-rate* cards, with *fee-only* versus *rate-only* cards as the reference decision type. For card usage, the dummy variable corresponds to *revolver-hard* trials, with *transactor* trials as the reference level. A positive coefficient indicates a higher probability of a decision being perceived as more difficulty. Each observation corresponds to a participant-choice. Columns 1 and 3 report the results using only the complexity metrics. Columns 2 and 4 include the complexity moderators: digit presentation and value similarity, and the latter's interaction with complexity. For digit presentation, the two dummy variables correspond to higher monthly spending levels ($1,500 and $1,800), with $1,000 as the omitted level. For value similarity, the dummy variable is for low value similarity. As certain combinations cannot be generated using the available credit cards in this study, the corresponding interaction terms are omitted, see Section II. Estimates are reported as log-odds ratios. Standard errors are clustered at the participant and choice level, and shown in parentheses.

while decision type had no effect (columns 3-4). Compared to *transactor* trials, participants were significantly more likely to perceive the decision as more difficult in *revolver* trials (column 4, *easy*: coeff = 4.62, s.e. = 0.57, $p < 0.001$; *hard*: coeff = 5.87, s.e. = 0.42, $p < 0.001$).

D. Individual sophistication and complexity

Lastly, we explore the role of individual sophistication, as defined by financial, debt, and risk literacy, and numeracy, in credit card decision-making. Table 5 presents the results. We find little evidence that individual sophistication improves performance in the choice task. Numeracy was the only measure positively associated with subjective difficulty, though the effect was marginal (columns 5-6: coeff = 0.01, s.e. = 0.01, $p < 0.05$), while none of the literacy measures correlated with choice quality or cognitive effort. This suggests that sophistication increases awareness of complexity but that even binary credit card choices may exceed the cognitive limits of consumers when unaided.

TABLE 5—INDIVIDUAL SOPHISTICATION

	Task performance		Average response time		Average difficulty rating	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	88.56	92.30	56.13	54.38	1.84	1.78
	(14.79)	(16.89)	(13.67)	(14.94)	(0.50)	(0.55)
Financial literacy	−0.16	−0.18	−0.08	−0.09	0.00	−0.00
	(0.09)	(0.10)	(0.08)	(0.09)	(0.00)	(0.00)
Debt literacy	0.01	0.04	0.04	0.04	0.00	0.00
	(0.07)	(0.08)	(0.07)	(0.07)	(0.00)	(0.00)
Risk literacy	0.13	0.12	0.11	0.13	−0.00	−0.00
	(0.06)	(0.07)	(0.06)	(0.06)	(0.00)	(0.00)
Numeracy	−0.17	−0.15	−0.26	−0.23	0.01	0.01
	(0.15)	(0.16)	(0.14)	(0.14)	(0.01)	(0.01)
Age		−0.21		−0.16		0.01
		(0.42)		(0.38)		(0.01)
Current ownership		5.53		5.34		0.25
		(7.31)		(6.46)		(0.24)
Past ownership		−4.89		1.19		−0.34
		(7.35)		(6.50)		(0.24)
R^2	0.27	0.31	0.27	0.37	0.21	0.30
F statistic	1.85	1.11	1.82	1.42	1.32	1.04
Participants	25	25	25	25	25	25
Observations	25	25	25	25	25	25

Note: This table reports the ordinary least squares (OLS) estimates of the effect of individual sophistication on aggregate behavioral measures in the choice task. The main independent variables are the four measures of individual sophistication: financial, debt, and risk literacy, and numeracy, with each defined by the participant's test performance (percent accuracy). The dependent variables are task performance, measured by the proportion of correct responses, in columns 1-2, cognitive effort, measured by the average total seconds spent on the trial screen, in columns 3-4, and subjective difficulty, measured by the average difficulty rating, where 1 indicates "very easy" and 5 "very hard", in columns 5-6. Each observation corresponds to a participant. Columns 1, 3, and 5 report the results using only the individual sophistication measures. Columns, 2, 4, and 6 include controls for age and current or past credit card ownership (binary indicators). Standard errors are shown in parentheses.

IV. Discussion

We introduced a formal framework to quantify the *computational* complexity of consumer decisions and demonstrated its behavioral implications in the context of credit card choice. Complexity was defined as the number of elementary computations involved in choosing the optimal credit card contract, which increases with (1) the number of rate-bearing options in the choice set and (2) the number of interest compounding periods over 12 months. Our framework shows that *revolvers*—those who carry a balance from month to month—face (weakly) greater complexity than *transactors*—those who always make full repayments—when choosing credit cards.

We tested this framework in a combined behavioral and eye-tracking experiment with 41 binary credit card decisions sampled from the Australian market, introducing two additional parameters: digit presentation and value similarity, to account for noisy information processing. Higher complexity, driven primarily by card usage, reduced choice quality while increasing cognitive effort, fixations, and perceived difficulty. Participants chose optimally in all *transactor* trials but approached random choice as computational demands grew, despite fixating more on the complexity-relevant feature, interest rates. The effect of complexity on performance was exacerbated by value similarity, while digit presentation affected only subjective difficulty. Individual sophistication, measured by financial, debt and risk literacy, as well as numeracy, was associated with greater awareness of decision complexity, but not with higher performance or reduced cognitive effort.

These findings are consistent with the notion that consumers are resource-limited computational systems and validate our framework as a tractable way to link the structural properties of consumer choices to behavioral outcomes. Unlike other complexity metrics used in the literature, such as the number of products or features, our measure isolates the specific operations that make evaluating and comparing options cognitively demanding. It predicts both objective and subjective difficulty, and can be generalized to more complex financial settings, such as mortgage and investment choices, as well as economic decisions, such as intertemporal choices, where present bias has been linked to complexity-induced information processing constraints (Enke, Graeber and Oprea, 2025).

The behavioral implications are economically meaningful. By removing uncertainty about future card use and binary choices, our design rules out alternative explanations based on present bias or overconfidence, or inattention. Yet even in this simplified setting, only 36 percent of participants outperformed the benchmark strategy, incurring an average loss of A$46 per decision, roughly equivalent to the average annual fee of *fee-rate* cards. Exponential growth bias also fails to account for these mistakes: linearizing interest computations would affect only the most complex decisions with high value similarity, whereas choice deviations occurred more broadly.

In real markets, where credit card decisions involve uncertainty and more complex features and options, these losses are likely larger. Prior estimates suggest that Australian *revolvers* forgo around A$250 per year by choosing suboptimal cards (Doyle, 2018) and collectively lose around A$468 million annually by not switching to lower-rate options (ASIC, 2024). Our results suggest that such losses may partly stem from complexity-driven valuation errors rather than mere behavioral biases. Importantly, complexity may exacerbate behavioral biases. For example, present-biased *revolvers* may overweight upfront fees and underweight future interest costs precisely because they struggle to compute long-term costs accurately. By contrast, the suboptimal behavior observed among wealthy cardholders in (Agarwal et al., 2015) likely reflects inattention to low-salience features rather than cognitive limits, since these consumers are typically *transactors* who face relatively simple, fee-based decisions.

These patterns raise a broader question: Are credit card features parameterized in ways that induce suboptimal choices? Because issuers derive most profits from interest charges rather than fees[10], they may have incentives—deliberate or not—to design card features that increase decision complexity, particularly for *revolvers*, whose mistakes are most costly. Prior studies show that issuers exploit consumer overconfidence by competing on salient upfront fees while maintaining high interest rates (Grubb, 2015; Ausubel, 1991). Given the structural trade-off between rates and fees, such pricing strategies reduce differentiation among options and increase the likelihood of costly mistakes. Consistent with this, our simulations show that many cards cluster around feature combinations that yield similar borrowing costs, making it harder for consumers to identify the optimal option. This provides a potential complexity-based explanation for the persistent stickiness of credit card interest rates, even in highly competitive markets such as the United States over the past four decades (Adams, Bord and Katcher, 2022; Ausubel, 1991; Bar-Gill and Bubb, 2012). While conjectures about feature parameterization, competi-

[10]Interest charges account for about 80% of credit card issuers' profitability, while usage charges, such as annual fees and late fees, make up around 5%, with the remainder coming from interchange charges (Adams, Bord and Katcher, 2022).

tion failures, and interest rate stickiness fall beyond the scope of this study, they highlight an important direction for future research.

Visual features, such as digit presentation in our study, can distort perceived difficulty even when they have minimal impact on computational demands or actual choice behavior. Firms may exploit this tendency by appealing to complexity-averse consumers through obfuscation, such as layering or hiding information about products to make them appear simpler than they are (see Consumer Financial Protection Bureau, 2023). Simplifying products in isolation (e.g., offering *fee-only* cards) may also backfire when competing products remain complex or difficult to compare. In our study, participants were more likely to err when choosing between *fee-only* and *rate-only* cards, despite having similar perceived difficulty and response times to *fee-only* versus *fee-rate* decisions of comparable complexity. This pattern mirrors a growing shift of *revolvers* toward buy-now-pay-later (BNPL) products (Consumer Financial Protection Bureau, 2025), akin to *fee-only* cards in this study, despite significantly higher borrowing costs.[11]

Finally, while financial education and disclosure remain essential, our findings highlight their limits when decisions exceed consumers' cognitive capacities. Even sophisticated participants failed to identify the optimal card once computational demands became significant. When valuation itself is complex, additional information alone is unlikely to improve outcomes unless it helps consumers translate product features into personalized costs and benefits (Bar-Gill and Bubb, 2012; Campbell, 2016; Seira, Elizondo and Laguna-Müggenburg, 2017). Future work should explore how financial technologies, such as open banking and artificial intelligence, can be leveraged to deliver personalized information and improve financial decision-making.

Our study has several limitations. It examines the complexity of credit card decisions in a simplified setting using binary choices, deterministic usage patterns, and a small sample of university students. Future research should incorporate uncertainty, additional feature dimensions such as reward benefits, and larger, more diverse samples to evaluate external validity. Nonetheless, the fact that even highly educated and financially literate participants struggled in this controlled setting underscores the importance of accounting for complexity in consumer choices, and in the design of financial products and policy.

[11]The average annualized interest rate across the two largest BNPL providers in Australia is approximately 36.43%, based on a $1,000 purchase with maximum late fees over repayment period, compared with an average credit card interest rate of 20.99% as of October 2025.

V. Conclusion

Understanding what drives suboptimal financial decision-making is important for improving consumer outcomes. This paper offers a complexity-based account of consumer mistakes, contributing to a growing literature on the role of complexity in consumer decision-making. We formally define complexity as the number of elementary computations involved in choosing the optimal option and test its implications in a combined behavioral and eye-tracking experiment using binary credit card choices. Complexity, primarily driven by card usage, impaired choice quality and increased cognitive effort, information acquisition, and perceived difficulty, disproportionately burdening *revolvers* who carry balances. These results show that even simple financial decisions can exceed consumers' cognitive capacities, limiting the effectiveness of information-based interventions. More broadly, our framework provides a basis for defining and quantifying decision and product complexity, identifying consumer groups most vulnerable to it, and informing policies that limit overly complex offerings.

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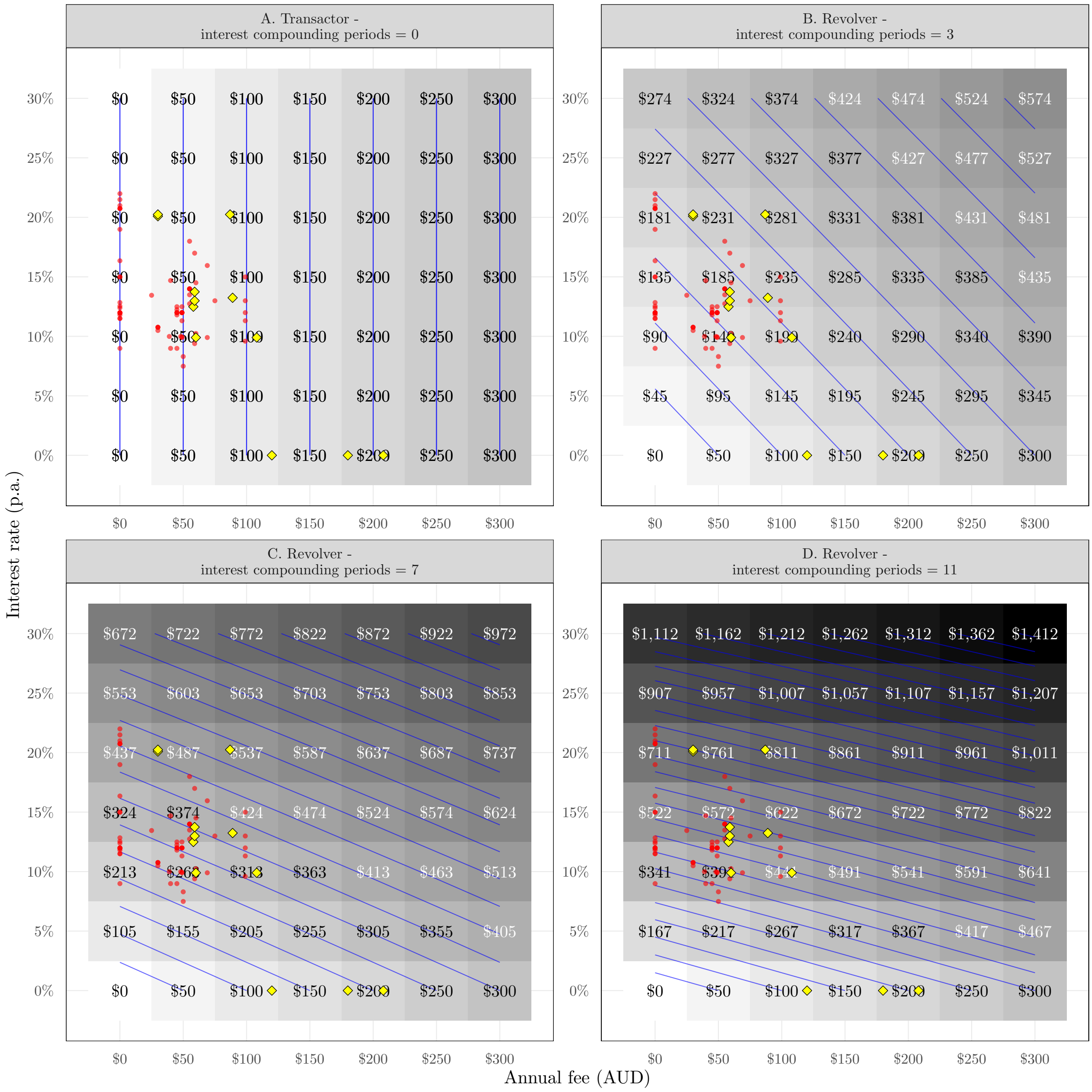
SIMULATED BORROWING COSTS OF SAMPLED CREDIT CARDS

In this section, we simulate borrowing costs of the 81 credit cards sampled in this study. Figure A1 illustrates the relationship between the annual fee and interest rate of the 81 sampled credit cards in Australia, and their corresponding borrowing costs across various revolving scenarios, assuming monthly purchases of $1,800 per month.[12] Borrowing costs are estimated based on the setup in our experiment, where monthly repayments equal to monthly purchases, unless otherwise specified. If the consumer repays in full every month, the optimal card is the one with the lowest annual fee, represented by the cards that lie on the leftmost blue line in panel A of Figure A1. Every card that lines on the same blue lie has the same value. However, if the consumer makes a minimum repayment in month t, then interest accrues over the next $12 - t$ months. For minimum repayment occurring in month nine, the optimal card is the bottom-leftmost red dot in panel B of Figure A1. In this scenario, many cards are within A$50 of the optimal card (each blue line represents a A$50 increase in borrowing costs), which reduces the differentiability of the optimal card from other options and increases the likelihood of making suboptimal choices, as discussed in the main paper.

[12]This is based on the average credit card balance in Australia (at the time of writing), where 70% of the personal accounts do not accrue interest (Reserve Bank of Australia, 2025).



Note: This figure shows the simulated borrowing costs of credit cards based on various annual fees and interest rates across four revolving scenarios, assuming monthly purchases of \$1,800. In panel A, the consumer is a *transactor* who always makes full repayments; in panels B to D, the consumer is a *revolver* who makes a minimum repayment in either month nine, five, one, respectively, while making repayments equal to monthly purchases in all other months. From left to right across the panels, the number of interest compounding periods for the consumer is zero, three, seven, and eleven. The dots represent the 81 credit cards sampled from the Australian market, with annual fees and interest rates as the key features. The yellow dots (14.8%) represent cards provided by the largest four banks in Australia. Each blue line indicates combinations of annual fees and interest rates that yield the same borrowing cost, spaced A\$50 apart. In each panel, the optimal credit card is one with the lowest borrowing cost. For example, in panel A, all *rate-only* credit cards that lie on the left most blue line incur the same, zero borrowing cost for the *transactor*.

FIGURE A1. SIMULATED BORROWING COSTS.

Experimental Instructions

Choosing a Credit Card Experiment

Instructions

Ethics: 25383

Summary

- This experiment aims to study how people choose credit cards.
- **Your objective is to maximise your performance by choosing the credit card with the cheapest borrowing cost from the displayed options.**
- This experiment involves eye tracking.
- You are NOT allowed to use any devices such as mobile phones or calculators.

Procedure and Incentives

- The experimental session consists of:
  1) Instructions
  2) 5 Practice Trials (not rewarded)
  3) 41 Experimental Trials (rewarded, see below)
  4) Questionnaire
- You will be rewarded for every correct experimental trial plus \$10 for showing up and \$5 for completing the entire experiment. Your total payout will take up to 7 business days to receive via PayID.
- The maximum payout is AUD\$40 (including the fixed participation fee of AUD\$15).

Task (1/4)

- In this experiment, you are asked to choose the credit card that gives you the lowest borrowing cost in a given 12-month period.
- Each credit card only has two features: **annual fee (\$)** and **interest rate (% p.a. [per annum]).**
- The total annual borrowing cost is defined as the annual fee plus any interest payments that incur during the12-month period.
- When you use a credit card, you are borrowing money from the credit card provider.
- **If you don't pay back the full amount of your credit card spending at the end of a month, you will be charged interest in the next month.**

Task (2/4)

- Interest payments are charged monthly depending on the closing balance in the previous month.
- That is, if you don't pay your monthly credit card balance in full in a given month, **you will be charged interest on that closing balance in the next month, as well as any amount you spend in the next month**.
- For example, if you spend \$1000 in January but only make a repayment of \$25, then in February, you will be charged interest on the closing balance of \$975 (\$1000-\$25) and any amount you spend in February.
- If the interest rate is 12% p.a. (i.e., monthly interest rate is 1%), then the monthly interest charges at the end of February will be \$9.75 if you make no other purchases (i.e., monthly spending = 0) in February.
- However, if you continue to spend \$1000 in February, then interest will incur on your monthly spending amount at the end of February as well, since you did not pay your previous month's credit card balance in full.

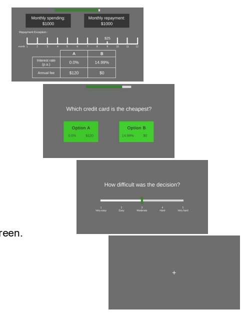
Task (3/4)

- You will make your repayment at the end of February to pay off your monthly credit card balance, which includes the interest charges on the previous month's closing balance and the amount you spend in February.
- **Note that your monthly repayment is used to pay off the total amount you owe to the credit card provider at the end of a given month, which includes any interest charges that may incur in that month.**
- Credit card incurs monthly interest charges as long as the closing balance in the *previous* month is greater than zero (i.e., you did not make a full repayment in the previous month).
- If you pay your monthly credit card balance in full, then you will not be charged interest in the next month.

Task (4/4)

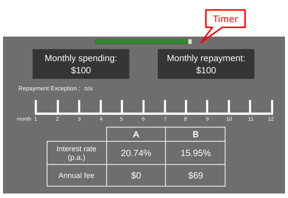
- The total interest payment over 12 months is the sum of all the monthly interest payments.
- The total borrowing cost of a credit card is the sum of its annual fee plus the total interest payment over 12 months.
- **Your objective is to maximise your performance in the experiment by choosing the credit card with the cheapest borrowing cost from the displayed options.**
- Only the correct experimental trials will be rewarded.

Example Trial



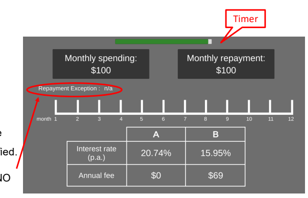
- A trial consists of four screens:
  1) Scenario
  2) Choice
  3) Difficulty Rating
  4) Rest
- The next few pages will explain the details of each screen.

1) Scenario (1/2)



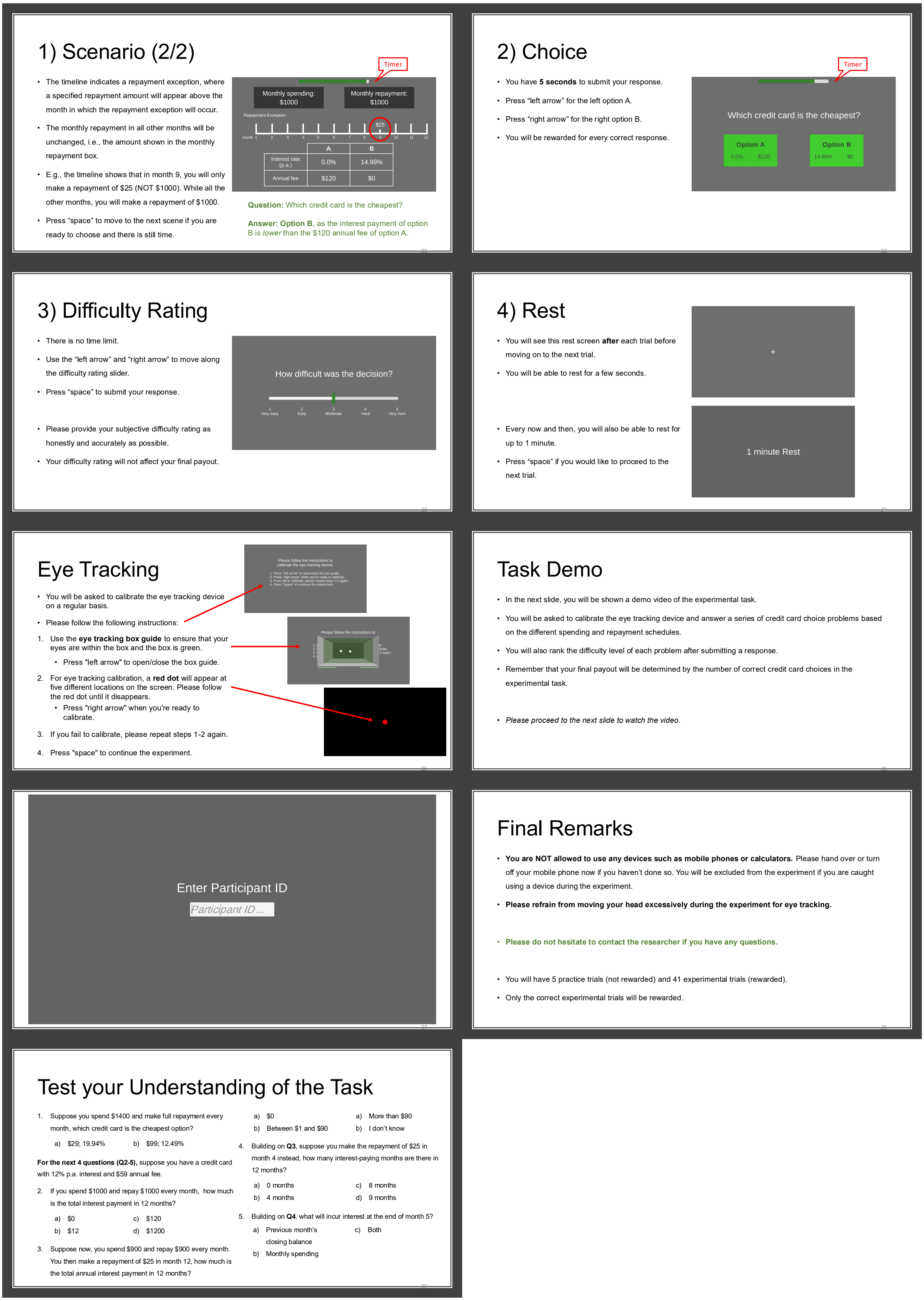
- You have **60 seconds** to read the scenario and decide which credit card option is the *cheapest*.
- Please pay attention to the **monthly spending, monthly repayment**, and **repayment exception**.
- The monthly spending and monthly repayment are constant over the **12-month period**, unless specified.
- Repayment exception: n/a indicates that there is NO repayment exception.
- There are two credit card options: A and B, with different interest rates and annual fees.

1) Scenario (1/2)



- You have **60 seconds** to read the scenario and decide which credit card option is the *cheapest*.
- Please pay attention to the **monthly spending, monthly repayment**, and **repayment exception**.
- The monthly spending and monthly repayment are constant over the **12-month period**, unless specified.
- Repayment exception: n/a indicates that there is NO repayment exception.
- There are two credit card options: A and B, with different interest rates and annual fees.


1) Scenario (1/2)
You have 60 seconds to read the scenario and decide which credit card option is the cheapest.
Please pay attention to the monthly spending, monthly repayment, and repayment exception.
The monthly spending and monthly repayment are constant over the 12-month period, unless specified.
Repayment exception: n/a indicates that there is NO repayment exception.
There are two credit card options: A and B, with different interest rates and annual fees.
Timer
Monthly spending: $100
Monthly repayment: $100
Repayment Exception : n/a
A
B
Interest rate (p.a.)
20.74%
15.95%
Annual fee
$0
$69
Remember that interest rates are quoted annually (p.a.)
1) Scenario (1/2)
You have 60 seconds to read the scenario and decide which credit card option is the cheapest.
Please pay attention to the monthly spending, monthly repayment, and repayment exception.
The monthly spending and monthly repayment are constant over the 12-month period, unless specified.
Repayment exception: n/a indicates that there is NO repayment exception.
There are two credit card options: A and B, with different interest rates and annual fees.
Timer
Monthly spending: $100
Monthly repayment: $100
Repayment Exception : n/a
A
B
Interest rate (p.a.)
20.74%
15.95%
Annual fee
$0
$69
Question: Which credit card is the cheapest?
1) Scenario (1/2)
You have 60 seconds to read the scenario and decide which credit card option is the cheapest.
Please pay attention to the monthly spending, monthly repayment, and repayment exception.
The monthly spending and monthly repayment are constant over the 12-month period, unless specified.
Repayment exception: n/a indicates that there is NO repayment exception.
There are two credit card options: A and B, with different interest rates and annual fees.
Timer
Monthly spending: $100
Monthly repayment: $100
Repayment Exception : n/a
A
B
Interest rate (p.a.)
20.74%
15.95%
Annual fee
$0
$69
Question: Which credit card is the cheapest?
Answer: Option A, you don't pay interest so you want the option with the lowest annual fee.
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Remember that interest is charged on the previous month's closing balance and the amount you spend in this month.
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Remember that monthly repayment pays off the monthly credit card balance, which includes any interest that may incur at the end of a month.
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Question: Given this timeline, how many months do you have to pay interest?
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Question: Given this timeline, how many months do you have to pay interest?
Answer: 3 months, as the closing balance in month 9 is non-zero!
1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press "space" to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Question: Which credit card is the cheapest?


1) Scenario (2/2)
The timeline indicates a repayment exception, where a specified repayment amount will appear above the month in which the repayment exception will occur.
The monthly repayment in all other months will be unchanged, i.e., the amount shown in the monthly repayment box.
E.g., the timeline shows that in month 9, you will only make a repayment of $25 (NOT $1000). While all the other months, you will make a repayment of $1000.
Press “space” to move to the next scene if you are ready to choose and there is still time.
Timer
Monthly spending: $1000
Monthly repayment: $1000
Repayment Exception :
$25
month 1 2 3 4 5 6 7 8 9 10 11 12
A
B
Interest rate (p.a.)
0.0%
14.99%
Annual fee
$120
$0
Question: Which credit card is the cheapest?
Answer: Option B, as the interest payment of option B is lower than the $120 annual fee of option A.
2) Choice
You have 5 seconds to submit your response.
Press “left arrow” for the left option A.
Press “right arrow” for the left option B.
You will be rewarded for every correct response.
Timer
Which credit card is the cheapest?
Option A
0.0% $120
Option B
14.99% $0
3) Difficulty Rating
There is no time limit.
Use the “left arrow” and “right arrow” to move along the difficulty rating slider.
Press “space” to submit your response.
Please provide your subjective difficulty rating as honestly and accurately as possible.
Your difficulty rating will not affect your final payout.
How difficult was the decision?
1 Very easy
2 Easy
3 Moderate
4 Hard
5 Very hard
4) Rest
You will see this rest screen after each trial before moving on to the next trial.
You will be able to rest for a few seconds.
Every now and then, you will also be able to rest for up to 1 minute.
Press “space” if you would like to proceed to the next trial.
+
1 minute Rest
Eye Tracking
You will be asked to calibrate the eye tracking device on a regular basis.
Please follow the following instructions:
1. Use the eye tracking box guide to ensure that your eyes are within the box and the box is green.
Press "left arrow" to open/close the box guide.
2. For eye tracking calibration, a red dot will appear at five different locations on the screen. Please follow the red dot until it disappears.
Press "right arrow" when you're ready to calibrate.
3. If you fail to calibrate, please repeat steps 1-2 again.
4. Press "space" to continue the experiment.
Please follow the instructions to calibrate the eye tracking device.
Task Demo
In the next slide, you will be shown a demo video of the experimental task.
You will be asked to calibrate the eye tracking device and answer a series of credit card choice problems based on the different spending and repayment schedules.
You will also rank the difficulty level of each problem after submitting a response.
Remember that your final payout will be determined by the number of correct credit card choices in the experimental task.
Please proceed to the next slide to watch the video.
Enter Participant ID
Participant ID...
Final Remarks
You are NOT allowed to use any devices such as mobile phones or calculators. Please hand over or turn off your mobile phone now if you haven't done so. You will be excluded from the experiment if you are caught using a device during the experiment.
Please refrain from moving your head excessively during the experiment for eye tracking.
Please do not hesitate to contact the researcher if you have any questions.
You will have 5 practice trials (not rewarded) and 41 experimental trials (rewarded).
Only the correct experimental trials will be rewarded.
Test your Understanding of the Task
1. Suppose you spend $1400 and make full repayment every month, which credit card is the cheapest option?
a) $29; 19.94%
b) $99; 12.49%
For the next 4 questions (Q2-5), suppose you have a credit card with 12% p.a. interest and $59 annual fee.
2. If you spend $1000 and repay $1000 every month, how much is the total interest payment in 12 months?
a) $0
b) $12
c) $120
d) $1200
3. Suppose now, you spend $900 and repay $900 every month. You then make a repayment of $25 in month 12, how much is the total annual interest payment in 12 months?
a) $0
b) Between $1 and $90
a) More than $90
b) I don't know
4. Building on Q3, suppose you make the repayment of $25 in month 4 instead, how many interest-paying months are there in 12 months?
a) 0 months
b) 4 months
c) 8 months
d) 9 months
5. Building on Q4, what will incur interest at the end of month 5?
a) Previous month's closing balance
b) Monthly spending
c) Both

QUESTIONNAIRE

In this section, we describe the questionnaire measuring participants' demographics, real-life credit card usage, and individual sophistication. The latter is assessed through established tests of financial, debt, and risk literacy, and numeracy. Specifically, participants completed the "Big Three" financial literacy questions from Lusardi and Mitchell (2014), the three-item debt literacy test from Lusardi and Tufano (2015), the Berlin numeracy test for risk literacy from Cokely et al. (2012), and the first ten questions of the numeracy test from Lipkus, Samsa and Rimer (2001)[13]. All demographic and credit card usage questions are listed below.

1) What is your participant ID?
2) What is your name?
3) What is your age?
4) Are you currently wearing contact lenses? [] Yes; [] No.
5) Which credit card feature did you pay most attention to during the experiment? [] Interest rate; [] Annual fee; [] I paid attention to both features equally; [] None; [] Other (please specify).
6) What strategy did you use to make a choice? For example, did you use a heuristic or rule of thumb to choose a credit card? How did you work out that one option has a cheaper borrowing cost than the other? What calculations, if any, did you use to compute the values of credit cards? *Please be as specific as possible.*
7) Do you have any feedback or comments about the experiment?
8) Do you currently have a credit card? [] Yes; [] No.
9) If "No":
    a) Have you owned a credit card in the past? [] Yes; [] No.
    b) What is stopping you from getting a credit card? *Select the most important reason:* [] I'm not interested in getting a credit card; [] I don't meet the financial requirements to apply for a credit card; [] I have a poor credit history; [] I don't want to have credit card debt; [] I don't understand how a credit card works; [] I think credit cards are bad (e.g., they fuel bad spending habits); [] Other (please specify).
10) If "Yes":
    a) How many credit cards do you own? [] 1; [] 2; [] 3 or more.
    b) How often do you pay your monthly credit card balance in full in the past 12 months? Select a category between 0 ("never") and 12 ("always") or "Prefer not to answer".
    c) Do any of your credit cards offer rewards, loyalty points, or other benefits? [] Yes; [] No.
    d) If yes, what is the annual fee of your main credit card? *(Type "n/a" if you don't know)*
    e) What is the annual interest rate of your main credit card? *(Type "n/a" if you don't know)*

[13]The final numeracy question was omitted due to a design oversight.

EYE-TRACKING SETUP AND DATA QUALITY

D1. Setup

Participants were seated approximately 65 cm away from a 23.8-inch EIZO FlexScan EV2451 monitor supplied by Tobii (monitor dimensions of 527 x 296.5 mm; resolution of 1,920 x 1,080 pixels), without head or chin support. The sampling frequency of the eye-tracker was 150 Hz. The experiment was programmed using the Tobii Pro SDK in Unity3D, with no overlapping areas of interest (AOIs). Before each trial, a fixation cross was presented at the center of the screen. Participants were not explicitly instructed to fixate on it.

D2. Data Quality

The raw data were preprocessed manually in Python following the Tobii I-VT fixation filter procedure (Olsen, 2012), followed by fixation classification with the I-VT classification algorithm by Dirk Gütlin (2021).

The data quality of the eye-tracking data is reported based on the eye movements on the fixation cross in the first, second, and last trials of the experiment. The average accuracy, precision, and root-mean-square of the eye-tracker were 3.05 degrees, 4.19 degrees, 0.52 degrees, respectively. Prior to pre-processing, the average data loss was 19.1%. After applying interpolation and noise reduction techniques to account for eye blinks and head movements, the average data loss decreased to 16.4%. Fixations shorter than 60 ms were excluded, as these were deemed insufficient for meaningful information processing. Trials with data loss exceeding 30% (204 trials) were excluded, along with five trials where the eye-tracking recording time was less than 95% of the response time. After these exclusions, we retained 80,780 fixations across 820 trials (80%) from 25 participants. Finally, we focused on fixations within the AOIs, resulting in 45,156 valid fixations (55.9%) for analysis.

DATA ANALYSIS

In this study, we estimate mixed effects models to examine the effect of computational complexity on credit card decision-making. For the behavioral measures, choice quality is modelled using generalized mixed-effects, cognitive effort with linear mixed-effects, and subjective difficulty with ordinal mixed-effects. All models include the four experimental parameters as independent variables, and a random intercept for each participant and trial.

We estimate the total effect of complexity using the following equation:

$$Y_{i,p} = \beta \log(\phi_i) + \eta V_i + \lambda(\log(\phi_i) \times V_i) + \sum_{n=1}^{2} \theta_n S_{n,i} + \alpha_i + \gamma_p, \tag{E1}$$

where the dependent variable $Y_{i,p}$ is one of the three behavioral measures: (i) choice quality, represented by a binary indicator for a correct response on trial i by participant p, (ii) cognitive effort, represented by the log of response time on the trial screen of trial i by participant p, or (iii) subjective difficulty represented by an ordinal variable for trial i by participant p, where 1 indicates "very easy" and 5 "very hard". Here, V_i is a binary indicator for whether the value difference between options exceeding \$20 for trial i, and S_n is a categorical variable representing the fixed monthly spending amounts in trial i, with $n \in \{1, 2\}$ corresponding to \$1,500 and \$1,800, respectively. We also include an interaction term between complexity and the value similarity of options, given our prediction that the effect of computational complexity is moderated by the differentiability of credit card options. Lastly, α_i is the random intercept for trial i and γ_p is the random intercept for participant p. The baseline trial (reference group) has high value similarity and a monthly spending of \$1,000.

Next, we decompose ϕ into the two complexity parameters: (1) the composition of card features in the decision (decision type) and (2) the number of interest compounding periods in card usage over 12 months. We estimate the following equation to assess the relative contributions of these two parameters to choice behavior in the choice task:

$$\begin{aligned} Y_{i,p} = &\sum_{j=1}^{2} \sum_{m=1}^{2} \beta_{j,m}(D_{i,j} \times K_{i,m}) + \eta V_i + \sum_{j=1}^{2} \sum_{m=1}^{2} \lambda_{j,m}(D_{i,j} \times K_{i,m} \times V_i) + \\ &\sum_{n=1}^{2} \theta_n S_{n,i} + \alpha_i + \gamma_p, \end{aligned} \tag{E2}$$

where $D_{i,j}$ and $K_{i,m}$ are categorical variables representing the type of credit card decision and the number of interest compounding periods in trial i, respectively. Specifically, $j \in \{1, 2\}$ corresponds to the following decision types, ordered by increasing computational complexity: *fee-only* vs. *fee-rate* and *rate-only* vs. *fee-rate* decisions, and $m \in \{1, 2\}$ corresponds to 4 and 9 interest compounding periods, corresponding *revolver-easy* and *revolver-hard* trials, respectively. The remaining variables are the same as in Equation E1. Given that it was not feasible to generate all combinations of the experimental parameters (as discussed in Section II), certain interactions between decision type, number of interest compounding periods, and value similarity will be excluded in the analysis. When interpreting the regression results, we refer to marginal effect as the estimated marginal mean or estimated marginal effect at the mean. Using the full dataset, the baseline trial (reference group) is a *transactor* trial with zero interest compounding periods comparing *fee-only* and *rate-only* cards with high value similarity, and a monthly spending of $1,000.

We estimate similar mixed-effects models for the eye-tracking data, but with only a random intercept for each participant, due to limited data to analyze choice-level variations (see Supplemental Appendix D.D2 for details about the eye-tracking data quality). Since value similarity is not visually presented in the choice task, we exclude this variable in this analysis. The dependent variable $Y_{i,p}$ is either: (1) the total number of AOI fixations in trial i by participant p or (2) the fixation gap between interest rates and annual fees in trial i by participant p.

SUMMARY STATISTICS

F1. Questionnaire

We benchmark participants' test scores against results from the existing literature. First, our participants demonstrated strong proficiency in basic numeracy and probability concepts, with correct response rates ranging from 88% to 100% across the ten numeracy questions. In comparison, the response rates in Lipkus, Samsa and Rimer (2001) for highly educated adults aged 40 and older ranged from 20.9% to 90.5%[14]. Second, while our participants struggled with more complex probability concepts, as reflected in their low performance on the risk literacy questionnaire (54%), they still outperformed the average university participant in Germany, whose average score in the Berlin numeracy test was 40%, as reported by Cokely et al. (2012). Third, our sample is more financially literate than the Australian population: 64% correctly answered all three of the financial literacy questions, compared to just 55% in the general population.[15] Lastly, in terms of debt literacy, our participants scored higher than the U.S. average on all three questions, with correct response rates of 68%, 60%, and 28%, compared to 35.9%, 35.4%, and 6.9%, respectively (Lusardi and Tufano, 2015). However, debt literacy remained low in our sample, underscoring the limited understanding of basic concepts related to borrowing and interest compounding—both of which are essential for making informed credit card decisions.

TABLE F1—SUMMARY STATISTICS OF MEASURES IN THE QUESTIONNAIRE.

Summary statistics	**N**	**Mean**	**St. Dev.**	**Min.**	**Max.**
Age	25	24.16	5.33	18	35
Current ownership	25	32.00%	47.61%		
No. of credit card holding	8	2.25	0.71	1	3
Past ownership	25	12.00%	33.17%		
Numeracy	25	93.60%	14.11%	50.00%	100.00%
Risk literacy	25	54.00%	32.02%	0.00%	100.00%
Financial literacy	25	85.33%	21.69%	33.33%	100.00%
Debt literacy	25	52.00%	25.60%	0.00%	100.00%

[14]In Lipkus, Samsa and Rimer (2001), the percentage of correct responses for each of the ten questions was: 55.3%, 59.8%, 20.9%, 78.2%, 83.6%, 90.5%, 86.6%, 80.8%, 77.5%, and 70.4%, respectively.

[15]Source: 2016 Household, Income and Labour Dynamics in Australia (HILDA) survey (Preston, 2020).

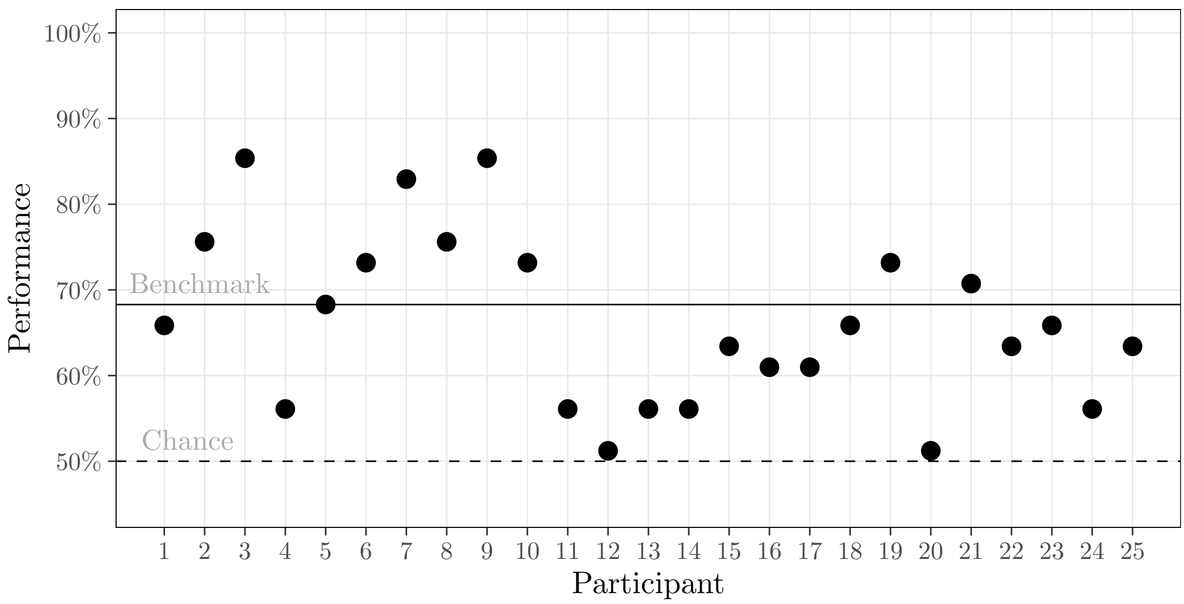
F2. Summary statistics of behavioral and eye-tracking measures in the choice task

We measure choice quality, cognitive effort, information acquisition, and subjective difficulty in the choice task, and the summary statistics are presented below.

TABLE F2—SUMMARY STATISTICS OF BEHAVIORAL AND EYE-TRACKING MEASURES.

Summary statistic	**N**	**Mean**	**St. Dev.**	**Min.**	**Max.**
Task performance	25	66.24%	10.00%	51.22%	85.37%
Response time (sec)	25	33.06	9.22	18.54	60
Subjective difficulty	25	2.89	0.32	2.22	3.71
Total number of fixations	25	49.77	20.40	13	92.72
Fixation gap between rates and fees	25	10.55	5.54	0	19.59
Total fixation duration (sec)	25	13.76	6.32	2.59	26.82
Single fixation duration (sec)	25	0.24	0.04	0.19	0.31

Note: Each of the 25 participants completed 41 trials in the choice task. All measures, except task performance, are averaged across valid trials. Task performance is measured as the proportion of correct responses across all trials. Response time is the amount of time a participant spends on the trial screen, with longer response times assumed to reflect higher cognitive effort. Subjective difficulty is measured using participants' self-reported difficulty ratings on a five-point Likert scale, where 1 indicates "very easy" and 5 "very hard". Total number of fixations is based on the number of valid fixation counts on the AOIs per trial, where a fixation refers to an event in which a participant looks at an AOI for at least 60 ms. Since fixations represent deliberate control of information search (Kahneman, 1973), higher fixation counts indicate greater information acquisition effort. To examine how participants acquire feature information, we also calculate the *fixation gap* between interest rates and annual fees of both options. A positive difference indicates more fixations on interest rates. We also include total and single fixation duration per trial, in seconds.



Note: Benchmark performance assumes a simple strategy of choosing the lower-fee option in *transactor* trials and lower-rate option in *revolver* trials.

FIGURE F1. INDIVIDUAL PERFORMANCE IN THE CHOICE TASK.