Improving Consumer Well-being: A Focus on Financial Health and Technology Adoption

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ABSTRACT

Humans have always faced threats, including physical, economic, and psychological harm from their environments. Unlike physical harm, psychological harm is less tangible and yet can lead to prolonged stress or mental illness. As society has evolved through technological advancements and increased complexity, so too has the nature of harm. Some threats, like the COVID-19 pandemic, have relatively clear and predictable consequences such as job loss and financial hardships, impacting both economic and psychological well-being. The digital age has introduced new types of harm associated with privacy violations and AI technology adoption. While people might have a vague idea of the negative consequences of such harm, they are often not certain about what specific harm they might encounter and how these could affect them in the future. Given the dynamics of harm, it is critical to understand both the impacts of harm that has already occurred and those that might occur in the future. The focus of this dissertation is on understanding psychological harm that consumers experience in two important domains—that of financial well-being and technology adoption. In essay 1, I study how consumers respond after missing a credit card payment and suggest an effective intervention to increase repayment. I find that providing an additional short period of time where any fees associated with missed payment are not levied increases repayment. I call this the "additional grace period" and demonstrate why it emerges. In essay 2, I investigate how consumers judge AI systems that use machine learning models that learn from customers' data to improve their performance. Although learning carries positive connotations associated with knowledge acquisition and personal growth, I find that consumers perceive a greater risk of using AI systems that are still learning compared to those that have completed learning. I document why this happens and explore the behavioral consequences.

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GENERAL AUDIENCE ABSTRACT

Humans have always faced threats, including physical, economic, and psychological harm from their environments. Unlike physical harm, psychological harm is less tangible and yet can lead to prolonged stress or mental illness. As society has evolved through technological advancements and increased complexity, so too has the nature of harm. Some threats, like the COVID-19 pandemic, have relatively clear and predictable consequences such as job loss and financial hardships, impacting both economic and psychological well-being. The digital age has introduced new types of harm associated with privacy violations and AI technology adoption. While people might have a vague idea of the negative consequences of such harm, they are often not certain about what specific harm they might encounter and how these could affect them in the future. Given the dynamics of harm, it is critical to understand both the impacts of harm that has already occurred and those that might occur in the future. The focus of this dissertation is on understanding psychological harm that consumers experience in two important domains—that of financial well-being and technology adoption.

In essay 1, I focus on consumers who have missed their credit card payments. The typical approach for firms is to levy higher fees on these consumers, which makes late or missed payments more expensive for consumers. On the contrary, I find that providing an additional short period of time where any fees associated with missed payment are not levied increases repayment. When this additional grace period is provided, consumers believe that they now have an opportunity to start afresh from the next cycle, increasing their motivation and debt repayment.

In essay 2, I study how consumers judge AI systems that use machine learning models that learn from customers' data to improve their performance. Although learning carries positive connotations associated with knowledge acquisition and personal growth, I find that the positive associations with human learning do not extend to AI learning. Instead, consumers perceive a greater risk of using AI systems that are still learning relative to those that have completed learning. This effect emerges because consumers feel exploited when AI systems learn from them believing that it could harm them in the future.

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1: INTRODUCTION

Consumer well-being is truly achieved when consumers are healthy, feel a sense of happiness, and are prosperous (Mick 2012). Factors contributing to consumer well-being extend across various domains including consumption, health, family, and financial matters (Bahl et al. 2016). In the digital age, with the growing integration of artificial intelligence (AI) in consumer's lives, technology also plays an important role in influencing consumer well-being. However, consumers also face many challenges. These challenges often hinder their well-being and ability to make full use of the opportunities that are available to them. In this dissertation, I study two of the biggest challenges that consumers face—one relating to financial decision-making, and the other, adapting to the digital age.

Americans carry a large amount of credit card debt—U.S. household credit card balance surpassed $1 trillion in the fourth quarter of 2024 alone (FRBNY 2024). Consequently, many consumers face financial stress, which the Covid-19 pandemic has further exacerbated (Dhue and Epperson 2023). A large credit card debt by itself is not a problem; in fact, credit card usage can help consumers smooth out their consumption and build a positive credit history. But the debt can become a problem if one is unable to repay it in full. Unfortunately, US credit card holders paid almost $117 billion in total interest and fees in 2020 alone including late fees and interest accrued on unpaid balance (CFPB 2022). Consumers also face technological challenges—they are often reluctant to adopt the latest technologies because they are unsure of how this would affect them in the future. With the growing integration of AI systems into various industries and daily life, a wide range of conversational AI systems has emerged. These are designed to provide a host of services ranging from answering questions to offering emotional support. However, on the other side, a great portion of Americans express concern about the growing use of AI in daily life (Pew Research Center 2022). This raises questions about what concerns consumers have when interacting with AI. My research focuses on the consumer of today. I identify psychological processes that today's consumers experience when dealing with financial and technological challenges and propose interventions to alleviate them.

In chapter 2, the first essay of this dissertation, I seek to understand how consumers respond after missing a credit card payment (i.e., late or missed payment) and suggest one intervention to promote repayment. While the typical approach for firms is to levy higher fees on these consumers (e.g., late fees or penalty APR), I find that providing consumers with an additional grace period—that is, an additional short period of time during which fees or penalties are not levied after the scheduled payment deadline—increases debt repayments relative to when penalties are immediately imposed. I demonstrate the effect across multiple experiments. I further identify consumers' belief of getting a fresh start as an underlying mechanism motivating consumers to increase repayment. Thus, contrary to normative expectations, I find that consumers repay more when it is less costly to do so.

In chapter 3, the second essay of this dissertation, I investigate how consumers judge AI services that use machine learning models that learn from users' data to improve their performance. While these AI-based systems can help consumers receive more personalized services, I find consumers perceive a greater risk of using AI systems that are still learning relative to those that have completed learning. I demonstrate this effect across a variety of contexts where AI-powered services are used. Extending beyond mere privacy concerns, I document the drivers of feelings of exploitation owing to AI learning. I also suggest a way to ameliorate future harm concerns associated with using AI systems with learning models.

Together, my dissertation helps identify important factors that hinder consumer well-being in two important domains—that of financial well-being and technology adoption. I also propose interventions that I believe can help nudge consumers into making better decisions. My research also provides prescriptive recommendations to managers and policy makers to help them improve not just consumer well-being, but also societal well-being.

CHAPTER 2: THE ADDITIONAL GRACE PERIOD EFFECT

ABSTRACT

Consumers often have difficulty managing their credit card debts. This is particularly true for individuals who miss their payments as they can easily be sucked into a vortex of debt from which escaping is difficult. While prior literature has identified several ways to promote debt repayment, not much is known about how to encourage repayment from consumers who failed to make a timely payment. This research documents an effective intervention to improve credit card debt repayment for consumers who have missed a payment. Evidence from eight preregistered studies shows providing indebted consumers with an additional grace period—additional short period of time during which any fees associated with missed payment are not levied—increases repayment. This additional grace period gives consumers an opportunity to start afresh, and this belief motivates them to repay their debts. These findings shed light on how consumers who fall behind on their payments repay their debts and provide an understanding of beliefs of fresh start helps debt repayment.

Americans carry a large amount of credit card debt. In the fourth quarter of 2023 alone, U.S. household credit card balance reached a new record high exceeding $1 trillion (FRBNY 2023). A large credit card debt by itself is not a problem; in fact, credit card usage can help consumers smooth out their consumption and build a positive credit history. But the debt can become a problem if one is unable to repay it in full. Unfortunately, most credit card users have difficulty repaying their credit card debt in full—about 82% of U.S. adults had a credit card in 2022, and half of them carried balances from month to month at least once in the prior year (FRB 2022). and many miss payments. Despite the prevalence of automated payment options, approximately 9% of credit card balances transitioned into delinquency in 2023 (FRBNY 2024). Consequently, U.S. credit cardholders paid about $12 billion in late fees in 2020 (CFPB 2022). What is worse is that those in lower income areas, who tend to have smaller balances when they are late on a payment, incur penalties that are often greater than their average daily balance (CFPB 2022).

Missing the first payment often leads one down the slippery slope of financial hardship. While missing one payment starts the process of delinquency, missing multiple payments has serious negative implications. Missing the first payment can start a chain of negative events: initially one just incurs unnecessary fees and interest, which could lead to multiple missed payments. Not surprisingly, about 7% of consumers have a credit card account that is past due (FRBP 2020). These missed payments soon end up hurting one's credit rating and can have deleterious effects on health (Gathergood 2012; Ong, Theseira, and Ng 2019; Richardson, Elliott, and Roberts 2013). In fact, credit card debt is the primary cause of financial stress (Dunn and Mirzaie 2016; Loibl et al. 2022). Thus, it is critical to help consumers who miss a payment because they can easily be sucked into a vortex of debt from which escaping is difficult—from one missed payment to serious delinquency.

While helping indebted consumers has clear implications for consumer welfare, they also impact firms and the society at large. Lenders frequently remove loans from their books because they are deemed uncollectable after delinquency (FRB 2024). These loans are then sold on the secondary market for pennies on the dollar (Minnesota Attorney General's Office; Nasdaq 2017), and only a small fraction is ever recovered. Uncollectable debts impose a huge burden on society, because ultimately, they have to be forgiven. For example, President Biden's student loan forgiveness program will cost taxpayers upwards of a trillion dollars (US House Budget Committee 2024).

How do firms recover unpaid debt? The typical approach for firms is to levy penalties on these consumers. The basic argument is that making it costlier for consumers who do not pay will lead to greater repayment. While the "stick" approach has been the accepted industry protocol since time immemorial, we believe that a "carrot" strategy might encourage greater repayment. Some firms have occasionally used such approaches. For example, Discover offered short-term payment assistance to its customers who were experiencing financial difficulty caused by the COVID-19 pandemic. Qualified customers might have been offered deferred payments and waived late fees for a couple of billing cycles (Tsosie 2023). However, the implications of these strategies are not well understood, and not surprisingly these approaches are not systematically used.

One potential shortcoming of the commonly used stick strategy is that it makes punishment salient. In this situation, after missing a payment, a consumer may try to lower the severity of the punishment by reducing the penalties incurred. In other words, their focus would be to reduce the severity of the blow, rather than to use this as an opportunity to make a positive change to their current situation. Because of this, we believe that the stick strategy will not lead to very high repayments relative to an alternate carrot strategy. We document a form of carrot strategy for consumers who have missed a payment and show its efficacy in evoking higher repayments relative to imposing penalties immediately. We propose providing these consumers an "additional grace" period—a short period of time after the scheduled payment deadline when penalties are not levied. During this additional grace period, consumers will get an opportunity to pay down some or all of the debt without incurring any additional fees. We propose that providing such an additional grace period will increase debt repayment. We delineate why this effect emerges and rule out alternative explanations.

It may be important to understand the proposed additional grace period in the context of current credit card operations. The U.S. Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009 requires credit card issuers to provide a period of at least 21 days to allow consumers to pay their bill after a billing cycle ends. This period is often referred to as the grace period. During this grace period consumers can make purchases using their credit card and do not incur any interest or late fees on the balance from the previous billing period and on new expenses. The CARD act stipulates that bills should be delivered to consumers at least 21 days before the payment is due. In alignment with this, credit card companies offer a penalty-free grace period typically lasting between 21 and 25 days after customers receive their monthly statements. We propose that providing an "additional" penalty-free grace period (vs. not) after the legally required 21-day grace period will increase debt repayment from those who missed their scheduled payment. At an aggregate level it will increase how many people pay off their entire debt, and it will also increase how much of their debt people repay.

Although our objective is to document the beneficial effect that additional grace period bestows on consumers relative to the current strategy of levying late fees and higher interest rate on the unpaid balance, we wanted to understand if this would be evident from an observer's perspective. Although the "carrot" approach bestows some advantages because it gives consumers more time to make a payment without incurring any fees or fines, normatively, one might still expect consumers who face increasing penalties on a daily basis to be more likely to make greater repayments. Afterall, every additional day delayed in making a payment increases incurred penalties. We conducted an exploratory study to understand an observers' perspective about the efficacy of these strategies. Using a between-subjects design, we informed respondents about a customer who had missed their monthly payment. In the control condition, we indicated that this customer will be charged a late fee of $29 along with an Annual Percentage Interest Rate (APR) of 24.74% on the unpaid balance, which will be calculated based on the number of days the amount is past due. In the additional grace period condition, respondents learned about the same penalties, but that the company will be giving the customer a 5-day period during which no penalties will be levied. Interestingly, observers did not believe that either strategy would outperform the other (see the appendix). This is not surprising given that respondents were unable to assess how others judge the same situation differently from themselves (Weaver et al. 2012). This could be one reason that managers who observe missed payments but do not experience it themselves may continue to rely on the incumbent "stick" strategy, without considering the merits of other approaches, such as our proposed "carrot" strategy. In subsequent studies, we ask respondents to play the role of consumers who have failed to make payments on time, and study how those experiencing the two strategies influence repayment decisions.

This research primarily contributes to the literature on consumer debt management (Amar et al. 2011; Bursztyn et al. 2019; Isaac, Wang, and Schindler 2021; Kettle et al. 2016). While prior research has identified several ways to promote debt repayment, not much is known about how to encourage repayment from consumers who failed to make a timely payment. This research also has important implications for public policy makers who want to prevent consumers from getting sucked into a debt induced vortex and for firms who want to encourage consumers to repay their debt. Credit card issuers can maximize the net earnings from unpaid accounts by granting an additional grace period during which all penalties are suspended. Admittedly, some credit card companies derive large revenues from late fees and interest payments and may not want to act in the best interest of society. However, if more consumers repay debts, then they may not have to sell these accounts to debt collection agencies for pennies on the dollar. Our findings also have other policy implications as they help provide deeper insights into the psychology of debt repayment, for example, the role of fresh start in helping debt repayment. We discuss these and other implications in the General Discussion. Next, we lay out our conceptual theory and detail our empirical investigation.

THEORETICAL BACKGROUND

Prior research has identified various ways to encourage debt repayment. This research can be segmented into three broad areas relating to the role of information, the role of incentives, and the nature of debt. The first stream of research documents how information and its framing can impact credit card repayment (Navarro-Martinez et al. 2011; Salisbury 2014; Steward 2009). For example, disclosing the “minimum required payment” on credit card statements has a boomerang effect on debt repayment—rather than increasing repayment, it paradoxically lowers amount repaid. This occurs because consumers anchor on the stated minimum amount (Steward 2009). However, displaying payoff time duration associated with these alternate payments (e.g., three-years to pay off the debt) can increase repayment as individuals recognize the burden that the longer payment duration imposes (Salisbury 2014).

The second stream examines the role of incentives in debt repayment (Bursztyn et al. 2019; Guiso, Sapienza, and Zingales 2013). At a fundamental level, moral attitudes towards default play a critical role in lowering mortgage default (Guiso, Sapienza, and Zingales 2013). Extending this research further, Bursztyn et al. (2019) finds that reminding credit card users of an ethical obligation to repay debt is more effective at inducing repayments relative to other incentives, such as financial or religious incentives.

The third stream of research documents the different suboptimal decisions that consumers make when repaying debt (Amar et al. 2011; Besharat, Carrillat, and Ladik 2014; Besharat Varki, and Craig 2015; Brown and Lahey 2015; Gal and McShane 2012; Gathergood et al. 2019; Isaac, Wang, and Schindler 2021). This stream shows that consumers often underweight critical factors, such as interest rates, and overweight other factors, such as the type of debt. For example, consumers pay off debt arising from hedonic purchases faster than those arising from utilitarian purchases (Besharat Varki, and Craig 2015). Similarly, they accelerate payment of the smallest debt (Amar et al. 2011; Besharat, Carrillat, and Ladik 2014), and debts with round numbers (Isaac, Wang, and Schindler 2021).

Although researchers have studied debt repayment, the literature does not yet offer much insight on how consumers who miss payments can be motivated to repay debt. Bursztyn et al. (2019) is an exception. Focusing on Indonesian customers who did not pay the minimum amount due at an Islamic bank, these researchers show that using a moral appeal (e.g., “non-repayment of debts is an injustice”) in reminder messages can be more effective at reducing delinquency relative to other appeals. We extend this research by documenting how providing an additional-grace period can increase repayment relative to the current strategy of imposing higher penalties immediately and provide a deeper explanation for why this occurs.

Missing a Credit Card Payment

To understand debt repayment after missing a due date, it may be important to understand the factors that underlie repayment decisions. Admittedly, people believe that it is their moral responsibility to repay debt—at least such kinds of appeals are more successful at inducing repayment relative to other appeals (Bursztyn et al. 2019). However, paying off debt requires more than just beliefs; it requires self-control and persistence. As is often the case with goals that require self-control and persistence, motivational forces play a crucial role. Not surprisingly, many of the strategies that help people repay debt also rely on increasing motivation to get out of debt (Brown and Lahey 2015; Gal and McShane 2012; Kettle et al. 2016; Ramsey 2013). For example, repaying a smaller debt first is better than making equivalent payments towards a larger debt. This is because being able to pay off a debt is perceived as a “win” which then motivates one to also pay off larger debts (Brown and Lahey 2015; Gal and McShane 2012; Ramsey 2013). These findings are consistent with other work that suggests that using a more concentrated debt repayment strategy that focuses on repaying one debt (usually the smallest one) is more successful than a more dispersed strategy, where multiple debts are simultaneously repaid (Kettle et al. 2016). A concentrated strategy focused on repaying the smallest debt elicits a greater sense of progress, which increases repayment motivation. However, once a payment is missed, penalties are immediately imposed, which explicitly signals that one has failed to manage debt repayment. This direct negative feedback that one is doing worse than one needs to might induce a range of negative feelings such as anxiety, distress, discouragement, or hopelessness. Consumers might be anxious not only about the immediate financial losses but also related potential negative outcomes such as significant drop in their credit score, having a bad reputation with credit card companies, or the concerns with managing their finances. Therefore, consumers who have missed their payment are likely to focus on such negative consequences, which might prompt them to lessen or avoid them.

A substantial body of research has shown that human behavior consists of two distinct classes of motivations, that is, approach and avoidance motives (Carver and Scheier 1990; Carver, Sutton, and Scheier 2000; Elliot 2008; Elliot and Church 1997). Approach motivation is characterized by energization of behavior toward the direction of a positive stimuli (i.e., desirable end-states or reward), whereas avoidance motivation is characterized by energization of behavior away from negative stimuli (i.e., undesirable end-states or punishment) (Elliot 2008). People who pursue approach goals are primarily concerned with accomplishment and advancement on the given task. In contrast, those who pursue avoidance goals are primarily concerned with duties and obligations (Brockner and Higgins 2001). As such, prior research has shown that approach orientation tends to lead to better performance than does avoidance orientation (Chan and Cameron 2012; Elliot, McGregor, and Gable 1999; Elliot and Church 1997; Gable 2006; Sullivan et al. 2006). For example, students who adopted avoidance goals, rather than approach ones, showed a decrease in both intrinsic motivation and graded performance (Elliot and Church 1997). In the context of job search, individuals driven by an approach-related motive tend to engage in job search to gain advancement and growth, even if they are satisfied with the current position. In contrast, individuals driven by avoidance-related motive search for a new job as a means to escape the negative aspects of the current position or organization (Zimmerman et al. 2012).

In our context, the best way to avoid undesirable outcomes (i.e., increasing penalties and the associated negative feelings) is to make the greatest repayment possible. However, we believe that when firms impose penalties or fines, consumers' attention will be diverted to avoiding these. The focus would be less on rectifying the situation completely and getting a fresh start. Instead, because the imposed penalties are unavoidable—they will be incurred immediately and reflected in the following statement—consumers are unlikely to feel the same amount of motivation to fully rectify the situation. Indeed, when one encounters impediments and believes that the perceived discrepancy between the actual and their desired states is unrecoverable, people are likely to disengage from further effort toward the outcome (Carver and Scheier 1988; Wrosch et al. 2003). In contrast, if consumers were given an opportunity to clean the slate and start afresh, they may be more motivated to pursue their goal.

Taken together, although one might normatively expect those without an additional grace period to repay more of their debt as they incur penalties, we argue that their repayment motivation will be depleted. This suggests that an intervention that helps consumers believe that they can produce a positive change rather than merely avoid worse outcomes can be beneficial. The additional grace period can provide that opportunity, as discussed next.

The Additional Grace Period Effect

The additional grace period is a distinct payment period granted to consumers who miss their payment. We propose that it allows them an opportunity to fix potential failure before it actually occurs. A rich literature documents how categorization influences inferences and evaluations (Cohen and Basu 1987; Goldstone 1994; Huang and Gong 2018; Huttenlocher, Hedges, and Prohaska 1992; Mishra and Mishra 2010; Tu and Soman 2014; Zhao, Lee, and Soman 2012). Categorization not only affects spatial judgments (e.g., people use state-based [vs. physical distances] categorization to assess disaster impact; Mishra and Mishra 2010) but also affects preferences (e.g., when numbers associated with a product breaches numerical category boundaries [e.g., 1001 vs. 1000], it induces higher arousal, which increases desire for the product; Huang and Gong 2018). More germane to our research, temporal categorization of tasks influences goal pursuit. For example, within-category versus across-category temporal deadlines (e.g., deadline in current vs. next month) result in greater task initiation (Tu and Soman 2014). Thus, categorization cues impact task inferences, which affects subsequent goal-directed behavior. We believe that giving consumers an additional grace period should have similar effects—following the end of the normal payment period, consumers transition into a period distinct from the previous one.

Past research suggests that consumers like to start afresh when entering a new period (Beshears et al. 2021; Dai, Milkman, and Riis 2014, 2015; Peetz and Wilson 2013). For example, those aspiring for a healthier lifestyle start visiting the gym at the beginning of a new year. As the start of a new year serves as a salient categorization cue on the calendar, it also elicits a desire to start afresh, which increases engagement in task-directed behavior (Dai, Milkman, and Riis 2014). The impact of time categorization on motivation is particularly strengthened when people experience a greater discrepancy between the current and desirable states (Dai, Milkman, and Riis 2015; Peetz and Wilson 2013; Wilson and Ross 2001). For consumers who have missed their payments, the potential for achieving a fresh start might not be fully realized if punishments are being transferred to the new period. By temporarily suspending penalties during this short-term period, the additional grace period will serve as a transitional phase that allows consumers to thwart their failures and start afresh in next cycles. In other words, if indebted consumers learn that they can still escape from failure by making use of this period, they are motivated to take advantage of this chance. Indeed, individuals who believe in their potential to attain positive outcomes orient toward the possibility of success and adopt approach achievement goals (Elliot and Church 1997; Elliot and Sheldon 1997). Thus, this fresh start motivation goes beyond simply trying to avoid extra costs; it involves a more proactive orientation towards completing a financial obligation successfully. Taken together, we propose that an additional grace period will create a fresh start opportunity, a chance to correct an impending failure and get a fresh start from the next period. And this belief of getting a fresh start will motivate consumers to take advantage of the additional grace period, which will increase repayment.

A natural question might be if simply extending the grace period by providing a longer window to repay debt accrued in every billing cycle (e.g., a 25-day window instead of a 21-day window) instead of providing an additional grace period after the grace period (i.e., creating two periods of time) would increase repayment. Unfortunately, past research suggests that extending the grace period would not increase repayment. In fact, longer time periods to repay loans have generally been shown to increase the likelihood of default (Carter et al. 2022; Dorfleitner and Oswald 2016; Field et al. 2013). Field et al. (2013) conducted a field experiment where respondents were either asked to initiate repayment within two weeks (vs. two months) after receiving their loan. While one might expect individuals with a two-month period to have more time to prepare for repayment, unfortunately it had a boomerang effect and default rates increased. Similarly, a longer repayment period for payday loans does not lead to higher initial repayments (Carter et al. 2022). Therefore, we suggest that instead of simply increasing the length of the normal grace period, giving indebted consumers an additional grace period (i.e., another distinct period) will increase repayment.

OVERVIEW OF STUDIES

We investigate the role of additional grace period in debt repayment in a series of eight preregistered studies. In study 1, we demonstrate that when consumers are provided with an additional grace period (vs. not) it does indeed increase debt repayment. In study 2, we replicate the additional grace period effect and examine how effective the additional grace period is in facilitating repayment compared to reminding consumers of the upcoming payment in advance. In studies 3A to 3D, we test the proposed underlying process: consumers who receive an additional grace period believe that they have a chance of getting a fresh start, which motivates them to repay the overdue credit card bill. In studies 4A and 4B, we provide additional evidence of the robustness of the additional grace period effect. In study 4A, we explore the role of additional grace period when consumers manage multiple credit card debts. Finally, in study 4B, we use an incentive-compatible design with a consequential outcome to examine the role of additional grace period. Participants were asked to repay their overdue credit card bill (with or without an additional grace period) in the presence of an attractive investment opportunity. Together the findings show that giving indebted consumers an additional payment period is an effective intervention for promoting repayment.

We followed the analyses plan and exclusion criteria described in the preregistrations. In the appendix, we provide all the stimuli and measures used in each study. We also include additional analyses for each study. These analyses incorporate individual difference variables such as gender, age, frequency of using credit cards, and payment history as covariates. Following our preregistrations, we only excluded respondents who failed the preregistered attention check question. In the appendix, we also report results including all respondents instead of ones that passed the attention check. In general, additional analyses including individual difference variables and all the participants were consistent with our predictions.

STUDY 1

Study 1 provides initial evidence: providing an additional grace period (vs. not) to consumers who miss a credit card payment will increase debt repayment. First, at an aggregate level, we expect more individuals to repay the entire debt amount. Second, at an individual level, consumers will also repay a higher amount. We report both the full payment rate and repayment amounts. We test this idea using a single-factor between-subjects design where all participants learned that they had missed a credit card payment but were either provided with an additional grace period or not. We then asked participants to indicate how much of their debt they would repay. The study was preregistered (https: https://aspredicted.org/L11_1JC).

Participants, Method, and Design

Following our preregistration, we recruited 300 MTurk participants through CloudResearch (48.3% female; M_{age} = 39.94). We administered one attention check question to assess participants' understanding of the scenario, "Do you have to pay the late fee if you pay your bill now?" (with a choice of "yes" or "no"). As preregistered, we excluded participants who failed to answer correctly. A final sample of 267 remained (49.1% female; M_{age} = 40.03).

We introduced participants to a credit card debt repayment scenario. All participants learned that they had used a credit card the previous month and the bill totaled $524. Although they could pay the entire amount, their budget was tight this month, and they were paying close attention to spending. Participants were then shown an email that they received from their credit card company informing them that their balance was now overdue. We then randomly assigned participants to one of two conditions. In the control condition, participants learned that along with a $35 late fee, they would also be incurring interest charges on the unpaid balance. In the additional grace period condition, participants received identical information about late fees and interest charges. However, they also learned that they have an additional one week during which if they paid their balance then they would not incur any late fees or interest charges. Participants could choose how much they wanted to repay. After reading the email from the credit card company, all participants were asked to indicate the amount of credit card bill they will repay now ("How much of your $524 credit card bill will you pay now?"). We then measured gender, age, and frequency of credit card use. We also measured two individual difference variables relating to tendency to pay their personal credit card debt ("I always pay my credit card balance off in full each month," "I often make only minimum payment on my credit card bill") on a 7-point scale (1 = strongly disagree, 7 = strongly agree). The second item was reversed and the responses to the two items were then aggregated to create a measure of payment history (Cronbach's alpha = .803).

Results and Discussion

Full Payment. We first conducted a binary logistic regression with condition (coded as control = 0, grace period = 1) predicting whether participants repaid the entire debt or not (paid in full = 1, not paid in full = 0). We use the same coding scheme across all studies. As expected, more people paid in full in the additional grace period condition (n = 151; 73.5%, SD = .44) than in the control condition (n = 116; 49.1%, SD = .50; B = 1.06, Wald χ^2 = 16.25, p < .001). The increase was very substantial (49.69%).

Amount Repaid. The Shapiro-Wilk test of normality revealed that the distribution of repaid amounts significantly deviated from a normal distribution (skewness = -1.18; Shapiro-Wilk's W = .80, p < .001). We, therefore, used a nonparametric test. Consistent with our expectations, participants in the additional grace period condition repaid more of their debt (M = $463.81, SD = $114.12) than those in the control condition (M = $398.91, SD = $151.09; Mann-Whitney U = 6542, z = - 4.09, p < .001, r = .25), resulting in a 16.27% increase.

Discussion. Taken together, study 1 documents support for our proposed additional grace period effect. An additional grace period promotes credit card debt repayment: it increases the likelihood of full repayment as well as the amount repaid. It is noteworthy that a large majority (almost 73.5%) of respondents in the additional grace period condition repaid the full balance. This is especially commendable considering that they did so even when they were not incurring any penalties. However, this is consistent with our expectations—consumers are less motivated to repay their debts when the penalties have already been imposed. As we propose, this is because they do not believe they will be able to get a fresh start and so are less engaged in goal pursuit relative to those in the additional grace period condition.

In the next study, we replicate the additional grace period effect and document how repayment decisions of those in the additional grace period condition differ from those who have not yet missed their payment.

STUDY 2

Study 2 extends the findings of study 1 in two ways. First, in the prior study, we used a 7-day additional grace period. In this study, we test if a shorter grace period can elicit the same pattern of results. The CARD Act of 2009 stipulates that a minimum period of 21 days needs to be offered to customers after closing of each billing cycle to repay their debt. But many credit card issuers provide longer periods of 25 days or more to repay their debt. This extended duration can be split into two periods—a 21-day period mandated by law followed by 4 days of an additional grace period. With this in mind, we shortened the additional grace period to 4 days. Second, in addition to the two conditions of study 1 where consumers already missed their payment but were either provided an additional grace period or incurred penalties and fees, we introduced a third condition where consumers had not yet missed their payment but instead received a reminder of an upcoming payment prior to their due date. Admittedly, these are two very different circumstances—in one situation (the first two conditions), consumers had already missed their payment deadline, whereas in the third condition, they still had time to pay. Our theory relates to the first two conditions where consumers had already missed a payment deadline, but this study provides us with an opportunity to compare our effects against the condition where consumers had not yet missed their deadline. Although our theory is silent on this, in addition to preregistering a prediction that the additional grace period will have a beneficial effect on repayment relative to the missed payment control condition, we also preregistered that the additional grace period will also have a beneficial effect on repayment relative to those who are simply being reminded of an upcoming payment (https://aspredicted.org/YY1_QVL).

Participants, Method, and Design

Per our preregistration, we recruited 450 participants on Prolific (48.4% female; M_{age} = 37.91). To ensure that all participants understood the scenarios, we included the same attention check as in study 1. As noted in preregistration, we excluded participants who failed the attention check question, leaving as a sample of 394 participants (49.7% female; M_{age} = 38.23).

Participants were introduced to a scenario where they learned that they had used their credit card last month and had amassed a bill of $604. They also learned that while their budget is tight this month, they could pay their entire credit card bill. We then randomly assigned participants to one of three conditions: missed payment control, missed payment with an additional grace period, and not yet missed payment. The two missed payment conditions were similar to those in study 1. Participants learned that they had missed their credit card payment, which was now overdue, and were either not provided additional information (i.e., control condition) or were given a 4-day additional period. In the third condition, participants were reminded that they had 4 days left until the payment due date. In all conditions, the consequences of not making a payment were the same: a $29 late fee and interest on the unpaid balance. Next, participants were asked to indicate the amount they would repay now ("How much of your $604 credit card bill will you pay now?"). Finally, as in study 1, we measured payment history using two items (Cronbach's alpha = .804) along with gender, age, and frequency of credit card use.

Results and Discussion

Full Payment. A binary logistic regression revealed a main effect of condition (Wald χ^2 = 21.55, p < .001). As predicted and consistent with our theory, more participants repaid the full amount in the additional grace period condition (n = 142; 74.6%, SD = .44) than in the missed payment control condition (n = 116; 49.1%, SD = .50; B = 1.11, Wald χ^2 = 17.32, p < .001). The increase was again quite substantial (51.93%).

Furthermore, the full repayment rate was also higher in the not yet missed payment condition (n = 136; 72.8%, SD = .45) than the missed payment control condition (B = 1.02, Wald χ^2 = 14.49, p < .001). However, contrary to our prediction, the full payment rate in the not yet missed payment condition revealed no difference from that in the additional grace period condition (B = .10, Wald χ^2 = .12, p = .726).

Amount repaid. As in study 1, the results of Shapiro-Wilk tests of normality revealed that the repaid amounts were not normally distributed (skewness = -1.55; Shapiro-Wilk' s W= .75, p < .001). We, therefore, used the nonparametric Kruskal-Wallis test for this analysis. The results revealed that the amounts repaid were different across the three conditions (H(2) = 20.67, p <.001). In order to test our hypotheses, we conducted planned contrast using the Mann-Whitney test. Supporting our additional grace period hypothesis, participants who were given an additional grace period (M = $530.75, SD = $143.78) made larger payments relative to those in the control condition (M = $473.66, SD = $157.36; Mann-Whitney U = 6260, z = -3.83, p < .001, r = .24), resulting in a 12.05% increase.

Participants who had not yet missed a payment made greater payment relative to those in the control condition (M = $537.56, SD = $132.16; Mann-Whitney U = 5928.5, z = -3.89, p < .001, r = .25). However, against our prediction, the repayment amount did not show a difference when compared to those in the additional grace period condition (Mann-Whitney U = 9610, z = -.09, p = .929, r = .01).

Discussion. These results are consistent with our theory and replicate the previous findings: providing an additional grace period to participants who missed a credit card payment increases debt repayment—it increases both likelihood of full repayment as well as payment magnitude. Interestingly, individuals who missed their payment but were not offered an additional grace period made less payment relative to those who had not yet missed their payment. Participants seemed less motivated to repay debt after missing a payment in the absence of interventions that encouraged them to do so.

Although our theory relates to those who missed a payment, this study also allows us to compare debt repayment behaviors of those who missed a deadline with those who did not miss their deadline. Although not critical to our theory, in our pre-registration, we had actually proposed that providing an additional grace period would also boost repayment relative to those who did not yet miss a payment. However, we did not find this effect. These results also contradict results from a pilot study. In the pilot study, we had used the same design but with a smaller sample (n = 300) of different respondents from the same survey platform, Prolific (49% female; M_{age} = 37.67). A total of 278 participants remained after the attention check (47.8% female; M_{age} = 37.80). A binary logistic regression revealed a main effect of condition (Wald χ^2 = 12.64, p = .002). Consistent with our theory, we replicated our core additional grace period effect. That is, among those who missed making a payment, providing an additional grace period increased the full repayment rate (n = 93; 78.5%, SD = .41) relative to the missed payment control condition (n = 92; 54.3%, SD = .50; B = 1.12, Wald χ^2 = 11.68, p < .001). Also, we used the nonparametric Kruskal-Wallis test for analyzing the amounts repaid. The results revealed that the amounts repaid were different across the three conditions (H(2) = 13.03, p = .001). The repaid amount was higher in the additional grace period (M = \$548.52, SD = \$124.50) than the missed payment control condition (M = \$477.16, SD = \$165.70; Mann-Whitney U = 3217, z = -3.47, p < .001, r = .26).

However, contradicting findings of the main study, we found that participants who were given an additional grace period after missing a payment made a greater payment compared to those in the not yet missed payment condition—the full repayment rate was higher in the additional grace period condition than the not yet missed payment condition (n = 93; 59.1%, SD = .49; B = .92, Wald χ^2 = 7.91, p = .005). Also, the repaid amount was higher in the additional grace period than the not yet missed condition (M = \$490.19, SD = \$164.14; Mann-Whitney U = 3457, z = -2.88, p = .004, r = .21).

To summarize, while the full payment rates (74.6% to 78.5%) and repayment amount (\$530.75 to \$548.52) did not show much of a change in the additional grace period condition across two studies, the numbers in the not yet missed condition did vary considerably (72.8% to 59.1%; \$537.56 to \$490.19). This is suggestive of the fact that individuals' repayment behaviors when they have not yet missed their payment may be influenced by personal and situational factors. Furthermore, we admit that comparing consumers who have missed a payment with those who have not is also not likely to be confound free. For example, in the not yet missed payment condition, it is unclear if the reminder alone was responsible for repayment—it is possible that at least some would have made a payment even if they did not receive a reminder. Nonetheless, based on these two studies, we can conclude that providing an additional grace period for those who missed their payment appears to be at least as effective in boosting repayments as reminding consumers of an upcoming payment.

STUDY 3A

The primary goal of study 3A is to provide support for the underlying process. We propose that people who are given an additional grace period (vs. not) are more likely to believe that they can get a fresh start from the next billing cycle, and this belief motivates people to repay their debt. The study uses a single factor design with two between-subjects conditions: an additional grace period and a control condition. The study was preregistered (https://aspredicted.org/M2N_JXW).

Participants, Method, and Design

Following our preregistration, we recruited 250 MTurk participants on CloudResearch (46% female; M_{age} = 43.62). As in the previous studies, participants were asked to respond to one question to assess their understanding of the provided information. As preregistered, we excluded 31 participants who failed the attention check question. A final sample of 219 remained (45.7% female; M_{age} = 43.96). As in our earlier studies, participants were told that they had used their credit card the previous month and had amassed a bill of $687, which was now past due. Participants were also made aware of the financial penalties involved, including a late fee of $35 and an interest charge on the unpaid amount. In the control condition, no further information was provided. In the additional grace period condition, participants were additionally informed that they have been provided with one week's grace period. If they pay within this week, they could avoid additional fees incurred on the unpaid balance.

After reading the scenario, participants were asked to indicate the amount that they would repay now ("How much of your $687 credit card bill will you pay now?") followed by a question assessing the motivation to pay off the entire outstanding debt ("How motivated are you to pay off all of your credit card bill now?") on a 9-point scale (1= not motivated at all, 9 = very motivated). Next, participants responded to three questions indicating their beliefs about getting a fresh start ("How much do you believe you have an opportunity to get a fresh start from the next billing cycle?," "How much do you believe you have an opportunity to get a new beginning from the next billing cycle?," and "How much do you believe you have an opportunity to clear your past credit card bill?") on a 9-point scale (1 = not much at all, 9 = very much). We combined these three items to create a measure of fresh start (Cronbach's alpha = .937). Lastly, as in previous studies, participants answered several questions about payment history (Cronbach's alpha = .716), frequency of credit card use, and provided demographic information.

Results and Discussion

Full Payment. A binary logistic regression revealed that more people repaid the full amount in the additional grace period condition (n = 122; 70.5%, SD = .46) than in the control condition (n = 97; 56.7%, SD = .50; B = .60, Wald χ^2 = 4.44, p = .035). The increase was again substantial (24.34%).

Amount Repaid. Because the responses were significantly skewed (skewness = -1.49; Shapiro-Wilk's W = .75, p < .001), we used a nonparametric test to compare the difference in repayment amounts between the two conditions. Consistent with our expectations, participants in the additional grace period condition repaid more of their debt (M = \$596.40, SD = \$162.65) than those in the control condition (M = \$557.66, SD = \$177.64; Mann-Whitney U = 5136, z = -1.96, p = .05, r = .13), resulting in a 6.95% increase.

Motivation to pay off debt. An ANOVA with motivation to pay off the entire debt revealed that participants in the additional grace period condition (M = 8.10, SD = 1.59) were more motivated to clear their past debt than those in the control condition (M = 7.58, SD = 2.05; $F(1, 217) = 4.51$, $p = .035$, $\eta_p^2 = .02$).

Fresh start. As expected, an ANOVA with fresh start revealed that participants in the additional grace period condition (M = 7.49, SD = 1.83) were more likely to believe that they had an opportunity to start afresh relative to those in the control condition (M = 6.72, SD = 2.24; $F(1, 217) = 7.89$, $p = .005$, $\eta_p^2 = .035$)

Mediation Analysis. Our theory predicts that participants in the additional grace period condition are more likely to believe that they have a chance to start afresh and this belief increases repayment. We tested the mediating role of starting afresh on our different dependent variables using PROCESS Model 4 with 5,000 bootstrap samples (Hayes 2013). Because the amount repaid is not normally distributed, we could not use this as a dependent variable in our analysis. We used the other two variables, full payment and motivation to pay off in full as our dependent variables. As expected, the belief of starting afresh mediated the effect of an additional grace period on full payment as the indirect effect was significant (indirect effect = .44, BootSE = .19, 95% CI = [.114, .874]). The direct effect was no longer significant (direct effect = .29, SE = .33, z = .88, $p = .378$). Using motivation to pay off debt in full also elicited a similar pattern of effects. Starting afresh mediated the effect of an additional grace period on motivation to pay off debt in full (indirect effect = .33, BootSE = .14, 95% CI = [.086, .644]). The direct effect of the additional grace period on motivation of clearing debt was however not significant (direct effect = .19, SE = .22, t = .87, $p = .385$). While we did not include a serial mediation analysis in our preregistration, we conducted one (model 6 with 5,000 bootstrap samples); condition (additional grace period vs. control) as the independent variable, full payment rate as the dependent variable, and an opportunity to start afresh and motivation to pay off debt as two serial mediators in this sequence. The results reveal that the serial mediation was significant (indirect effect = .63, BootSE = .34, 95% CI = [.166, 1.496]). The mediation via an opportunity to start afresh alone was still significant (indirect effect = .28, BootSE = .15, 95% CI = [.063, .669]).

Discussion. Study 3A expands our investigation in two ways. First, consistent with prior studies, this study documents support for the additional grace period effect. The additional grace period not only increased the number of people who repaid in full, it also increased the amount repaid as well as increased respondent's motivation to repay the debt. Importantly, the results confirm our theorized process: beliefs of starting afresh underlies the additional grace period effect.

STUDY 3B

Our goal for study 3B is to rule out an alternative process explanation based on reciprocity. It is possible that customers who benefit from an additional grace period might feel ingratiated toward the credit card company, leading them to increase repayments as a way of reciprocation. Reciprocity in social exchanges is fundamentally produced by the psychological experience of indebtedness, a state of tension that motivates individuals to repay others (Flynn and Yu 2021; Gouldner 1960; Greenberg and Shapiro 1971). In our study's context, however, it is possible that customers in both conditions might feel equally indebted to the credit card company. After all, both groups of customers have borrowed from the company and have an outstanding debt—they have violated their financial obligations. Thus, the sense of indebtedness, and consequently the feeling of reciprocity, could be present in equal measure in both groups of consumers.

In this study, we measured the proposed underlying mechanism and the sense of reciprocity to test whether the effect is driven by the belief of getting a fresh start. The study thus uses a single factor design with two between-subjects conditions: an additional grace period and a control condition. The study was preregistered (https://aspredicted.org/M3T_VCV).

Participants, Method, and Design

Per our preregistration, we posted 250 slots on Prolific, and 251 participants enrolled in our study (46.2% female; M_{age} = 37.64). We included the same attention check item as in previous studies. As preregistered, participants who failed to pass this question were excluded from analysis, leaving us with 223 participants (45.7% female; M_{age} = 37.93). We employed a study design similar to the one used in the previous study with a few differences. We changed the amount due to $826 and we reduced the additional grace period to 4 days. Except for the additional information provided in the additional grace period condition, all participants read the same information. Participants then indicated how much of their credit card bill they would pay now ("How much of your $826 credit card bill will you pay now?"), and how motivated they are to repay the entire credit card bill ("How motivated are you to pay off all of your credit card bill now?"; 1= not motivated at all, 9 = very motivated).

Next, we measured beliefs about starting afresh using the same three questions that we used in study 3A, which we combined together (Cronbach's alpha = .93). Participants then responded to three questions indicating their level of agreement about the email from the credit card company to measure their sense of reciprocity toward the company ("I feel like I owe the credit card company," "I feel like I am indebted to the credit card company," and "I feel like I should reciprocate for what the credit card company has provided for me") on a 9-point scale (1 = strongly disagree, 9 = strongly agree). We combined these three items to create a measure of a sense of reciprocity (Cronbach's alpha = .788). Finally, as in our previous studies, participants indicated their payment history with two items (Cronbach's alpha = .818) along with gender, age, and frequency of credit card use.

Results and Discussion

Full Payment. A binary logistic regression revealed that more people repaid the full amount in the additional grace period condition (n = 116; 71.6%, SD = .45) than in the control condition (n = 107; 57%, SD = .50; B = .64, Wald $\chi^2 = 5.09$, $p = .024$). The increase was again quite substantial (25.61%).

Amount Repaid. Because the distribution of the amount repaid was skewed (skewness = -1.23; Shapiro-Wilk's W = .75, $p < .001$), we used a nonparametric test. Consistent with our previous findings, participants in the additional grace period condition repaid more of their debt (M = \$699.90, SD = \$226.53) than those in the control condition (M = \$646.36, SD = \$235.64; Mann-Whitney U = 5333, z = -2.12, $p = .034$, r = .14), resulting in an 8.28% increase.

Motivation to pay off debt. Consistent with study 3A findings, an ANOVA with motivation to pay off debt elicited a main effect of condition ($F(1, 221) = 4.17$, $p = .042$, $\eta_p^2 = .019$). Participants in the additional grace period (M = 7.78, SD = 2.01) were more motivated to clear their past bill than in the control condition (M = 7.17, SD = 2.49).

Fresh start. An ANOVA with fresh start elicited a main effect of condition ($F(1, 221) = 13.18$, $p < .001$, $\eta_p^2 = .056$). Participants were more likely to believe that they would have an opportunity to start anew in the additional grace period condition (M = 7.28, SD = 1.88) than in the control condition (M = 6.29, SD = 2.22).

Mediation Analysis. We conducted a mediation analysis using PROCESS (Model 4, number of bootstrap samples: 5000) to test the role of beliefs about starting afresh in impacting the additional grace period effect. Consistent with the prior findings, the path from condition (additional grace period vs. control) to full payment was significantly mediated by beliefs of starting afresh (indirect effect = .50, BootSE = .17, 95% CI = [.216, .888]). The direct effect from condition to the proportion who repaid the full amount was however no longer significant (direct effect = .23, SE = .32, z = .70, p = .483). A similar mediation analysis with motivation led to similar results. Motivation to clear past debt was significantly mediated by beliefs of starting afresh (indirect effect =.53, BootSE = .17, 95% CI = [.214, .877]). The direct path from condition to motivation was no longer significant (direct effect = .09, SE = .27, t = .33, p = .741). While we did not include a serial mediation analysis in our preregistration, we conducted one (model 6 with 5,000 bootstrap samples); condition (additional grace period vs. control) as the independent variable, full payment rate as the dependent variable, and an opportunity to start afresh and motivation to pay off debt as two serial mediators in this sequence. The results reveal that the serial mediation was significant (indirect effect = .67, BootSE = .28, 95% CI = [.304, 1.369]). The mediation via an opportunity to start afresh alone was still significant (indirect effect = .28, BootSE = .18, 95% CI = [.012, .694]).

Sense of reciprocity. We conducted an ANOVA with a sense of reciprocity as the dependent variable and condition as the independent variable. Feelings of reciprocity did not differ between the two conditions ($M_{add'l.grace}$ = 6.11, SD = 2.26 vs. $M_{control}$ = 6.55, SD = 1.95;

$F(1, 221) = 2.42$, $p = .121$, $\eta_p^2 = .011$). Thus, feelings of reciprocity cannot explain the additional grace period effect.

Discussion. This study provides support for our proposed process, while ruling out an alternative reciprocity-based explanation. Next, we investigate anticipated regret as another alternative explanation.

STUDY 3C

Our goal for study 3C is to eliminate an alternative process explanation based on anticipated regret. Another possible explanation could be that people make payments during the additional grace period to avoid the regret of missing this opportunity. However, we believe that this account cannot fully explain our proposed effect. This is because we expect both groups of people to feel similar levels of regret. First, people in the control condition should experience regret if they do not make payments because further delays would result in increasing penalties. Second, those in additional grace period may also experience anticipated regret for not taking advantage of the opportunity. However, unlike regret, we believe that the belief of getting a fresh start differs between the two conditions and has a more fundamental influence on repayments. In this study, we measured both the proposed underlying mechanism and anticipated. The study was preregistered (https://aspredicted.org/2hht-3ks5).

Participants, Method, and Design

We posted 300 slots on Prolific, and 300 participants enrolled in our study (47.3% female; $M_{age} = 39.74$). We included the same attention check item as in previous studies.

Participants who failed to pass this question were excluded from analysis, leaving us with 257 participants (48.2% female; M_{age} = 40). We employed the same study design as in the previous one. After measuring dependent variables and beliefs about starting afresh, participants responded to three questions indicating their anticipated regret for not making payments now ("How much regret will you feel if you do not pay your credit card bill now?", "How bad will you feel if you do not pay your credit card bill now?", and "How uncomfortable will you feel if you do not pay your credit card bill now?") on a 9-point scale (1 = not much at all/not bad at all/not uncomfortable at all, 9 = very much/very bad/very uncomfortable). We combined these three items to create a measure of anticipated regret (Cronbach's alpha = .921). Finally, we measured individual differences and demographic information.

Results and Discussion

Full Payment. A binary logistic regression revealed that more people repaid the full amount in the additional grace period condition (n = 138; 69.6%, SD = .46) than in the control condition (n = 119; 44.5%, SD = .50; B = 1.05, Wald χ^2 = 16.03, p < .001). The increase was substantial (56.40%).

Amount Repaid. Consistent with our previous findings, participants in the additional grace period condition repaid more of their debt (M = \$717.75, SD = \$203.52) than those in the control condition (M = \$621.95, SD = \$236.21; Mann-Whitney U = 6098, z = -3.96, p < .001, r = .25), resulting in a 15.40% increase.

Motivation to pay off debt. Consistent with prior findings, an ANOVA with motivation to pay off debt elicited a main effect of condition (F(1, 255) = 5.78, p = .017, η_p^2 = .022).

Participants in the additional grace period (M = 8.16, SD = 1.50) were more motivated to clear their past bill than in the control condition (M = 7.64, SD = 1.96).

Fresh start. An ANOVA with fresh start elicited a main effect of condition ($F(1, 255) = 6.89$, $p = .009$, $\eta_p^2 = .026$). Participants were more likely to believe that they would have an opportunity to start anew in the additional grace period condition (M = 7.29, SD = 1.75) than in the control condition (M = 6.68, SD = 1.98).

Mediation Analysis. We conducted a mediation analysis using PROCESS (Model 4, number of bootstrap samples: 5000) to test the role of beliefs about starting afresh in impacting the additional grace period effect. Consistent with the prior findings, the path from condition (additional grace period vs. control) to full payment was significantly mediated by beliefs of starting afresh (indirect effect = .23, BootSE = .11, 95% CI = [.051, .493]). This time the direct effect from condition to the proportion who repaid the full amount was no longer significant (direct effect = .93, SE = .28, z = 3.37, $p = .0007$). A similar mediation analysis with motivation led to similar results. Motivation to clear past debt was significantly mediated by beliefs of starting afresh (indirect effect =.28, BootSE = .12, 95% CI = [.062, .541]). The direct path from condition to motivation was no longer significant (direct effect = .24, SE = .19, t = 1.26, $p = .207$). Similar to the prior study, we conducted a serial mediation analysis. The results reveal that the serial mediation was significant (indirect effect = .24, BootSE = .14, 95% CI = [.050, .583]). The mediation via an opportunity to start afresh alone was no longer significant (indirect effect = .10, BootSE = .07, 95% CI = [-.019, .267]).

Anticipated regret. We conducted an ANOVA with anticipated regret as the dependent variable and condition as the independent variable. Anticipated regret did not differ between the two conditions ($M_{add'l.grace}$ = 7.08, SD = 2.08 vs. $M_{control}$ = 6.99, SD = 2.12; $F(1, 255) = .125$, p = .724, $\eta_p^2 = .000$). Thus, anticipated regret cannot explain the additional grace period effect.

Discussion. This study again replicates our proposed process, while ruling out an alternative explanation based on anticipated regret.

STUDY 3D

Some might argue that the proposed effect arises simply because people want to avoid additional charges. While we do not deny that this motivation could play a role—after all, clearing such charges may help people feel as if they are starting fresh by leaving past failures behind—it does not fully explain why people make a large payment when given the additional grace period. If the sole motivation were to avoid penalties, then people without an additional grace period should also pay as much as they can, and thus, we should expect the same level of payment in both conditions, because their charges continue to accumulate.

Nonetheless, to assess if the desire to avoid penalties solely drives the proposed effect, in this study, in addition to our standard two conditions, we also added a new condition, which we refer to as payment-based penalty condition. In our regular grace period condition, all fees are waived—participants do not incur a penalty for paying late nor do they incur additional interest fees. However, in the new payment-based penalty condition, we also provide an additional grace period, but during this period if participants make a payment, then while they will still incur interest-based penalties, they will not incur a late fee. Thus, while we are providing them with some benefits, if avoidance of paying fees underlies our effects, then we should see higher repayments in this condition because their repayment amount directly determines the amount of total charges. The study was preregistered (https://aspredicted.org/8cj4-5nd8).

Participants, Method, and Design

We posted 450 slots on Prolific, and 450 participants enrolled in our study (49.1% female; M_{age} = 39.76). We included the same attention check item as in previous studies. Participants who failed to pass this question were excluded from analysis, leaving us with 392 participants (49.2% female; M_{age} = 40.05). We employed the same study design as in the previous ones regarding the prior two conditions. In the payment-based penalty condition, participants learned that an additional 4-day grace period is given. If they make a payment within this period, while their interest charges will be adjusted accordingly based on their payment, they will not incur the late fee. We measured the amount of payment and collected demographic information.

Results and Discussion

Full Payment. A binary logistic regression revealed a main effect of condition (Wald χ^2 = 6.23, p = .044). Consistent with our theory, more participants repaid the full amount in the additional grace period condition (n = 141; 71.6%, SD = .45) than in the control condition (n = 109; 57.8%, SD = .50; B = .61, Wald χ^2 = 5.16, p = .023). The increase was substantial (23.88%). Furthermore, the full repayment rate was also higher in the payment-based condition (n = 142; 70.4%, SD = .46) than the control condition (B = .55, Wald χ^2 = 4.28, p = .039). However, the full payment rate in the payment-based condition revealed no difference from that in the additional grace period condition (B = .60, Wald χ^2 = .05, p = .823).

Amount repaid. The amounts repaid were not different across the three conditions (H(2) = 4.15, $p = .125$). We conducted planned contrasts using the Mann-Whitney test. Participants who were given an additional grace period (M = \$722.45, SD = \$236.37) made larger payments relative to those in the control condition (M = \$686.78, SD = \$237.61; Mann-Whitney U = 6786, z = -1.87, $p = .061$, r = .12), resulting in a 5.19% increase. Although not significant, participants in the payment-based grace period condition made greater payment relative to those in the control condition (M = \$716.28, SD = \$246.96; Mann-Whitney U = 10516.50, z = -1.01, $p =$ .311, r = .06). In addition, the repayment amount did not show a difference when compared to those in the additional grace period condition (Mann-Whitney U = 10974, z = -.683, $p = .495$, r = .04).

Discussion. This study demonstrates that the proposed effect cannot be solely explained by the desire to avoid paying fees. While the full payment rate in the payment-based grace period condition was greater than that in the control condition, the rate was not greater than that in the original grace period condition. These findings suggest that although people may wish to avoid extra fees and could achieve this by making a larger payment, this alone does not fully explain why they make such significant payments when given the additional grace period. In the appendix, we also report another study that rules out several other alternative explanations, such as perceived importance, urgency, and feelings of regret about not making a payment on time. None of these explained the additional grace period effect.

STUDY 4A

While many Americans own at least one credit card (> 80%), most own more (an average of 3.9 credit cards; Horymski 2024). In such instances consumers may have to allocate their budget across different cards that have different due dates. The goal of study 4A is to assess how consumers with multiple credit cards respond to an additional grace period. We consider a situation where one of the credit cards is past due (with or without an additional grace period) while the other is not yet past due. This setting enables us to examine if a credit card with an additional grace period is prioritized in debt repayment over the not-yet-due card. We also test the robustness of the additional grace period effect by creating a tradeoff where the interest rate associated with the not-yet-past due card is higher than the past-due card. We expect the grace period effect to still persist. The study was preregistered (https://aspredicted.org/PKC_H86).

Participants, Method, and Design

Per our preregistration, we recruited 200 participants on Prolific (49.5% female; M_{age} = 36.55). We included the same attention check question as in previous studies to assess participants' understanding of the credit card fee structure. As pre-registered, we excluded participants who failed to respond to this question correctly from the analysis. A final sample of 188 remained (47.9% female; M_{age} = 37.18).

We employed a single-factor (an additional grace period vs. control) between-subjects design. All participants learned that they had used two credit cards last month, a Mastercard and a Visa, and have two bills to pay. They owed $416 on the Mastercard, which was due in a week's time. If not paid on time, they would incur a $29 late fee and interest charges on the unpaid balance (APR 21.99%). They also owed $409 on the Visa card, which was past due. Because the

Visa bill was overdue, they would incur a $23 late fee and interest charges on the remaining balance (APR 19.99%). Additionally, participants in the additional grace period condition learned that they received a 7-day grace period, which will expire in 1 day.

Next, all participants indicated how they would allocate their current budget ($700) towards paying down these two credit cards ("Please indicate the amount of each credit card bill you will pay now"). The response format required them to use up the entire $700 toward paying the two bills. Lastly, as in previous studies, we asked participants about their payment history (Cronbach's alpha = .811) and recorded gender, age, and frequency of credit card use.

Results and Discussion

Full Payment. Given that our focus was on how grace period impacts payment of the Visa card, we conducted a binary logistic regression with full payment rate of the Visa card. Although not significant, more people repaid the amount in full in the additional grace period condition (n = 97; 53.6%, SD = .50) relative to the control condition (n = 91; 40.7%, SD = .49; B = .52, Wald $\chi^2 = 3.14$, $p = .076$). The increase was substantial (31.70%).

Amount Repaid. Our focus is on understanding repayment of the overdue Visa card bill. Because repaid amounts violated normality (skewness = -.24; Shapiro-Wilk's W = .77, $p < .001$), we used non-parametric tests. Although not significant, consistent with our expectations, participants in the additional grace period condition (M = $360.61, SD = $57.74) repaid a greater amount relative to those in the control condition (M = $346.73, SD = $58.79; Mann-Whitney U = 3835.5, z = -1.68, $p = .093$, r = .12), resulting in a 4% increase.

Follow-up to Study 4A. Although the effects were consistent with our expectations, the results were not significant. After conducting the study and our analyses, we realized that we did not have enough power to test our effects (used G*Power to compute the achieved power; Power (1 – β err prob) = .422 for a two-tailed test, .548 for a one-tailed test). So, we reran the study with a new pool of MTurk respondents through CloudResearch and increased the sample size to 300 (301 completed the study; 47.8% female; M_{age} = 40.25). We also made one other change: we reduced the late fee on the not-yet-due card from $29 to $26. Using the preregistered criteria, we excluded participants who failed the attention check question. A final sample of 259 remained (46.3% female; M_{age} = 40.80). A binary logistic regression with full payment rate of the Visa card showed that more people repaid the amount in full in the additional grace period condition (n = 142; 60.6%, SD = .49) relative to the control condition (n = 117; 36.8%, SD = .48; B = .97, Wald χ^2 = 14.26, *p* <.001). The increase was again quite substantial (64.67%). Participants in the additional grace period condition also repaid a greater amount of the Visa credit bill (M = $368.89, SD = $55.11) relative to those in the control condition (M = $343.46, SD = $57.80, Mann-Whitney U = 6180, z = -3.86, *p* < .001, r = .24), resulting in a 7.4% increase.

Discussion. Study 4A and its follow-up together demonstrate the robustness of the additional grace period. Participants took advantage of the grace period even when (1) they had another credit card bill that was due but whose payment deadline they could meet and (2) when the extra fees associated with the overdue bill was lower than that of the one not overdue.

STUDY 4B

The primary goal of study 4B is to test our effect using an incentive compatible design with monetary incentives. Participants could use their budget to repay debt or invest in the market. Participants could earn performance-based bonuses. The incentives were designed to award a larger bonus when more of the budget was directed toward the investment. Thus, this study was a conservative test of the additional grace period as the alternative option could generate higher returns. The study was preregistered (https://aspredicted.org/JR8_HPN).

Participants, Method, and Design

Following preregistration, we recruited 350 MTurk participants through CloudResearch (51.4% female; M_{age} = 42.72). We asked one question to assess their understanding of the credit card fee structure used in the scenario, “If you pay the credit card bill now, will the late fee appear on the statement?” As preregistered, we excluded participants who failed to pass this question from our analyses. A final sample of 318 remained (52.5% female; M_{age} = 43.32).

At the outset, participants learned that they would take part in a financial simulation game where their task is to distribute the given budget between paying their debt and investing. They were also informed that we will randomly select 20 participants and award a bonus payment based on their final balance after the budget allocation decision. Following instructions on how their final balance will be calculated, they took part in a simulated example. We asked two questions based on the example to assess their understanding. As per the preregistration (and as explained to participants), they could only participate in the simulation game if they answered both questions correctly. Otherwise, they were not allowed to participate in the study and were directed to the end of the survey.

In the simulation game, all participants learned that they lived in a foreign country that uses a currency called UTY(Ͼ) and that their current budget was Ͼ800. They could use this money to pay an overdue credit card debt and/or invest in the stock market. We then randomly assigned participants to one of two conditions. In the control condition, participants were informed that they would be charged a late fee and their APR may increase because of the missed payment. In the additional grace period condition, while participants received the same information about the fee structure, they also learned that they had received an additional three-day grace period, which would expire the following day. If they paid their balance within this period, the penalties would not be imposed.

Next, all participants were informed about an investment opportunity. The return will be realized next month. Participants learned that the average return would be 27% and that on average a ₠100 investment would be ₠127. However, this was an average and their return could be higher or lower. We determined the average return based on a random draw from a normal distribution (minimum: -25.43%, maximum: 80.92%, std: 16.94%). Thus, each individual's return would vary depending on the draw and could be higher or lower. However, on average, investing in the market would generate a higher final balance than paying off their credit card bill.

Participants were asked to indicate how they would allocate their current budget (₠800) towards paying down the credit card and/or investing in the stock ("Please indicate how you are going to spend your available budget"). The response format required them to use up the entire ₠800. After they distributed their budget, we drew randomly from our distribution and then presented the simulation game outcomes for each participant. The outcome included the rate of return, the total return from their stock investment, the remaining credit card balance, and the final balance at the end of the month. We randomly selected 20 participants and gave them a payout based on their final balance. We then measured payment history as in the previous studies (Cronbach's alpha = .816), willingness to take investment risks ("When thinking of your financial investments, how willing are you to take risks") on a 9-point scale, recorded gender, age, and frequency of credit card use.

Results and Discussion

Full Payment. A binary logistic regression with full payment as the dependent variable revealed that more people repaid the full amount in the grace period condition (n = 161; 78.9%, SD = .41) relative to the control condition (n = 157; 68.8%, SD = .46; B =.53, Wald χ^2 = 4.16, *p* = .041). The increase was substantial (14.68%).

Amount Repaid. Because amount repaid violated normality (skewness= -1.77; Shapiro-Wilk's W= .61, *p* < .001) we subjected the data to a nonparametric test. Although marginally significant, consistent with our expectations, participants in the additional grace period condition repaid more of their debt (M = €516.34, SD = €182.42) relative to those in the control condition (M = €487.45, SD = €197.24; Mann-Whitney U = 11464.5, z = -1.86, *p* = .064, r = .10), resulting in a 5.93% increase.

Discussion. Study 4B demonstrates the additional grace period effect in an incentive-compatible setting where participants can earn real monetary incentives based on their decisions. While participants could earn a larger bonus by investing more money in stock, a larger number of participants in the additional grace period condition chose to sacrifice the potential for a larger bonus in order to repay their debt.

GENERAL DISCUSSION

Consumers miss credit card bill payments for a variety of reasons, which could range from simple forgetfulness to financial duress. However, regardless of the cause, missing a payment initiates a series of negative consequences. Consumers who miss payments often belong to lower economic strata (Haughwout et al. 2022) and lack educational and financial resources (Allgood and Walstad 2013; Lopes 2008). Missing a payment can easily suck these individuals into a vortex of debt from which escaping is difficult. The current research documents an effective intervention to improve debt repayment for consumers who missed the scheduled payment deadline.

We demonstrate that granting an additional grace period— during which late fees and interest rates are not levied—facilitates credit card debt repayments. Our findings show that providing an additional grace period not only increases the likelihood of full payment and average amount repaid, but also motivates consumers to pay off the overdue debt. Together nine preregistered studies including one preliminary study provide converging evidence for the additional grace period effect. Study 1 demonstrates the basic additional grace period effect. Study 2 replicates the additional grace period effect and examines its effectiveness in promoting repayment compared to a reminder of the upcoming payment. Studies 3 show that the additional grace period effect is driven by consumers' beliefs about getting a fresh start. An additional grace period gives indebted consumers an opportunity to start afresh, which increases motivation to repay. Study 4A and its follow up provides more evidence of the robustness of the additional grace period by showing that the effect persists when consumers have multiple credit card bills that need to be paid. Finally, study 4B corroborates these findings by showing that the effect holds for incentive-compatible decisions. Taken together, we show that the additional grace period effect is robust across eight studies. The effect is consistent across different credit card bill amounts, fee structures, and the length of the additional grace period. In addition, our findings hold not only in hypothetical credit card scenarios but also in incentive-compatible settings.

Although our research demonstrates the robustness of the additional grace period effect, we are cautious about generalizing this approach to all contexts involving deadlines. In each case, policymakers consider what should be prioritized. For example, offering some types of carrot strategy may be perceived as unfair to those who consistently complete tasks on time. Moreover, there are various ways to design a carrot strategy—such as providing extra time suspending penalties, as we did, adjusting penalty structures, or even introducing an alternative task to offset failure in the prior one. Our findings remain inconclusive when applied to specific contexts. We believe that the effectiveness of any type of new approach depends on what truly motivates people to achieve outcomes—such as reciprocity which we ruled out, social desirability, or self-presentation—and these underlying mechanisms may influence outcomes and the persistence of effects in different ways.

We believe that credit card companies can take advantage of the additional grace period effect by making a few small tweaks to the existing payment policy. Under the CARD Act of 2009 credit card companies are required to offer at least a 21-day payment period to consumers to repay their debt after closure of their monthly bill. Many companies, however, provide a period that is longer (e.g., 25 days) than the minimum legally required period. Our proposed additional grace period can be offered by breaking this duration into two periods: a legally required 21-day grace period followed by an "additional grace" period of 4 to 7 days during which the penalties (additional fees) are not levied. We expect that categorizing this duration will allow firms to successfully leverage the additional grace period.

Theoretical Implications

Our findings allow us to make several theoretical contributions. First, our main theoretical contribution is to the literature on debt repayment (Amar et al. 2011; Besharat, Varki, and Craig 2015; Bursztyn et al. 2019; Gathergood et al. 2019; Kettle et al. 2016; Salisbury 2014; Steward 2009). Prior research has identified several ways to encourage debt repayment—these range from framing of information displayed in credit card statements (Salisbury 2014; Steward 2009) to appealing to consumers' higher morality (Bursztyn et al. 2019; Guiso, Sapienza, and Zingales 2013) and to examining suboptimal debt repayment decisions (Amar et al. 2011; Besharat, Carrillat, and Ladik 2014; Gathergood et al. 2019). However, the literature does not yet provide much insight on how consumers who miss payments can be motivated to repay debts (Bursztyn et al. 2019 is an exception). To the best of our knowledge, this research is one of the first to examine decision-making of consumers who missed a scheduled credit card payment and delineates an effective intervention to promote repayment.

Our findings also align with prior research on suboptimal debt repayment decisions. Consumers often underweight critical factors such as interest rates or the extent of penalties when making repayment. For example, as suggested by Amar et al. (2011), consumers tend to pay off small debts first to reduce the number of debt accounts even when the larger debts may have higher interest rates. In study 4A and its follow-up, we show that the additional grace period effect persists even when individuals had another credit card bill whose payment deadline they could meet. Although it was more cost effective to pay more towards the not-yet-past-due card (because interest rates were higher), we find a contrarian effect. Consistent with findings from Amar et al. (2011), when an additional grace period was not provided, there was no difference in full payment rate between the two credit card accounts that had nearly identical debts ($409 and $416) (40.7% vs. 39.6%; p = .908). When the additional grace period was provided, however, more individuals paid off the entire bill (53.6%) relative to the not-yet-past-due bill (30.9%; p = .015), despite the lower interest rates. While we agree that other factors such as real or anticipated changes to credit ratings may play a role, our findings show that the availability of an additional grace period affects how individuals allocate their budget.

Lastly, our research contributes to the literature on approach-avoidance motivation (Carver and Scheier 1990; Carver, Sutton, and Scheier 2000; Elliot 2008; Elliot and Church 1997) by introducing a new nudge to help individuals have approach-motivation. When individuals center their self-regulation efforts around avoiding negative outcomes, it can lead to reducing belief in their competence to achieve the goal (Elliot and Sheldon 1997). Our studies also show that the repayment dropped significantly when participants missed a payment in the absence of interventions that encouraged them to do so. We extend this stream of research by showing that offering an opportunity for a fresh start can recover belief in one’s ability to achieve desired outcomes and encourage prompt actions toward those outcomes.

Our findings are suggestive of four future research avenues. First, our research focuses on an understudied customer segment—consumers who missed a payment. Because these individuals often belong to lower socio-economic segments (Haughwout et al. 2022), we hope our work will provide impetus to study decision-making of such individuals and identify other interventions to help these individuals manage their debts more effectively.

Second, future research could examine other aspects of the additional grace period. In our operationalization, both the late fees as well as the interest charged were suspended. Perhaps other changes in the fee structure could also be beneficial—for example, charging a late fee but not levying interest on unpaid balance. One could conceivably also make the opposite argument—not charging a late fee but levying higher interest rates may be even more beneficial. Prior research suggests that altering interpretation of goal failure helps goal reengagement (Fishbach, Dhar, and Zhang 2006; Soman and Cheema 2004). Imposing a late fee may give the impression that an individual is still "a late payer". Perhaps levying higher interest rates but without a late fee may be interpreted differently? Future research could examine the interplay between these elements and its impact on repayment to design a better fee structure.

Third, it may be insightful to consider other contexts where the additional grace period effect might emerge. Consumers often procrastinate committing to future events, which often leads to suboptimal financial decisions. For example, consumers who miss the "early-bird" price at events (e.g., at conferences or to sporting events) could benefit if an additional grace period was provided to still receive the initial pricing. This could increase booking rates and also lead to greater engagement and satisfaction.

Finally, future research could also explore if consumers might adapt and adjust behavior if they become aware that the additional grace period is a recurring event. For example, consumers who received the additional grace period in the past might expect it again in the future. Would this then just be interpreted as an extended payment period? We believe that as long as consumers view this period as an "opportunity" to get a fresh beginning from the next cycle, our effect will sill persist. We do admit that the additional grace period effect has the potential of becoming less impactful over time, if offered indiscriminately. However, it does confer many benefits. First, for many individuals, the cycle of debt starts with but a missed payment. The additional grace period can help these consumers, at least the first time. Importantly, it would certainly help delay consumers from falling into the vortex of debt. Second, many consumers are able to manage their budgets most times and occasionally need a helping hand. The additional grace period can benefit these consumers. While there still may be some who might interpret the additional grace period as an extended period during which they can make payments, banks and credit card agencies can limit the number of times they offer the additional grace period. This will ensure that consumers do not take this for granted.

Practical Implications

Our findings also have important implications for public policy makers who want to protect consumers from getting sucked into a debt induced vortex. Credit card users may have difficulty managing their credit card debts, especially when faced with unexpected expenses or changes in their financial circumstances. For example, the COVID-19 pandemic has had a significant impact on the economy and many people have faced financial challenges as a result. The pandemic has made it more difficult for credit card holders to make payments on time due to job loss, reduced income, or other financial strains (Konish 2021). Offering an additional grace period on credit card payments can help these consumers and others.

Second, our findings have other policy implications as they help provide deeper insights into the psychology of debt repayment—for example, the role of fresh start in helping debt repayment. In studies 3A and 3B, we find that an additional grace period gives indebted consumers an opportunity to start afresh, which drives greater debt repayment. This suggests once consumers learn that they can escape from failure and start anew, they are more likely to take the next step to improve their financial circumstances. Policy makers can devise other creative ways to help consumers believe that they can get a clean fresh start in the future.

Our findings also have implications for firms who want to encourage consumers to repay their debt. Some credit card companies generate significant revenues from late fees and interest payments and may not want to act in the best interest of society. Ensuring an active and engaged customer base can be financially beneficial even for these companies. This is because delinquent accounts are costly. When consumers are unable to repay their debt, credit card companies sell these delinquent accounts to debt collection agencies for pennies on the dollar. In 2024, the market size of the U.S. debt collection agencies is measured at $20.9 billion (IBS World 2024). If more consumers repay their debts, then credit card companies will generate higher revenues. In addition, some credit card companies offer financial assistance programs, many of them are temporary and customers are required to demonstrate a genuine and legitimate financial hardship such as unemployment, natural disaster. And it remains unclear what qualification criteria they use to identify eligible customers. Thus, companies could potentially benefit from the additional grace period by reducing costs associated with managing this hardship program.

In summary, we document an effective intervention to improve credit card debt repayment for consumers who have missed a payment. We propose that providing an additional - grace period will increase debt repayment. We delineate why this effect emerges and rule out alternative explanations. Helping indebted consumers has implications for both consumer and societal well-being.

CHAPTER 3: THE LAB RAT EFFECT: WHY DO HUMANS ABHOR BEING A TEST SUBJECT FOR AI MACHINES

ABSTRACT

With the growing integration of AI systems into various industries and our daily lives, consumers are increasingly engaging with conversational AI systems. These are designed to provide a host of services ranging from answering questions to offering emotional support. Many of them employ machine learning algorithms that learn through conversations with consumers to enhance their performance, which occurs without explicit human guidance. Although learning carries positive connotations associated with knowledge acquisition and personal growth, we show that the positive associations with human learning do not extend to AI learning—humans do not wish to be the lab rats from whom AI systems learn and grow. Instead, individuals feel exploited when AI systems learn from them. Across six experiments, we show that consumers perceive a greater risk of using AI systems that are still learning relative to those that have completed learning. Extending beyond mere privacy concerns (e.g., information leakage, unauthorized use), we document the drivers of these feelings of exploitation (e.g., owing to AI learning). Our research identifies a critical psychological barrier that consumers face when engaging with AI systems and has important policy implications surrounding AI learning.

“I am still learning,” the famous quote attributed to Renaissance artist Michelangelo implies that the pursuit of knowledge is endless and there is always more to learn. Progress made across diverse disciplines, from research to technology, is a testament to our continuous pursuit of learning. However, it was not until recently that people realized that humans are not the only entities capable of continuous learning. Algorithms embedded in AI systems also learn. They use complex mathematical models to learn from human data to improve their performance; this occurs endogenously without explicit human guidance (Brown 2021, Mahesh 2020).

We use the term AI or AI system to refer to systems that use any kind of machine learning algorithm to generate recommendations or predictions for users through interactive conversations with them. One such example is conversational AI systems, such as chatbots or virtual assistants. The global conversational AI market is expected to grow to $41.39 billion by 2030 (Grand View Research 2025). Consumers who interact with AI systems are aware that AI systems learn from them and adapt based on these communications. For example, ChatGPT, a natural language processing AI, comprehends human language and attempts to mimic human interactions, owing to extensive training using a vast amount of human data (Ben 2023). ChatGPT informs users that conversations with the system may be reviewed by its AI trainers to improve the system. Additionally, services like Replika, a virtual AI companion, and Woebot, an AI-based mental health support service, operate through conversations with users. They highlight in their applications that they learn and evolve with each conversation.

Typically, learning carries positive connotations; it is associated with knowledge acquisition and personal growth. Humans believe learning to be the cornerstone of human evolution; learning and adaptation have helped the human species survive and thrive (Boyd, Richerson, and Henrich 2011). Like human learning, learning is fundamental for the growth and improvement of AI systems. It is based on a training process where algorithms identify patterns from a large training dataset (Mahesh 2020). These training data sets are typically sourced from publicly available information (Leffer 2023). Additionally, AI systems also learn through conversations with users. For examples, ChatGPT or Replika has already been trained using a large dataset, but it still learns from customers by chatting with them to continue to develop their algorithms. While learning is critical for development of AI systems, ultimately, human adoption of specific AI systems is critical to its acceptance and success.

We propose that while learning carries positive associations, this may only be restricted to situations where humans learn, but not where AI systems learn from humans. Using a common metaphor, humans do not wish to be the lab rats from whom AI systems learn. Specifically, we posit that consumers judge AI-based systems that are still learning (vs. have completed learning) as riskier to use. This is because they do not wish to be test subjects whose data are used to enhance AI capabilities, which could then cause future harm. Indeed, AI uses their data to generate new knowledge, and users know little about how this new knowledge will be created, used, and who the beneficiary will be. These concerns will induce feelings of being exploited.

Our research makes two fundamental contributions. First, we contribute to research on artificial intelligence (or algorithm) aversion (Castelo, Bos, and Lehmann 2019, Dietvorst, Simmons, and Massey 2015, Longoni, Bonezzi, and Morewedge 2019, Luo et al, 2019, Önkal et al. 2009, Promberger and Baron 2006) by focusing on perhaps the most central features of AI systems, the ability to learn and enhance their performance. Our findings also contribute to research on consumers' privacy issues (Culnan and Armstrong 1999, Martin and Murphy 2017, Smith, Dinev, and Xu 2011) by identifying a novel psychological mechanism that shapes the use of AI beyond privacy concerns.

THEORETICAL BACKGROUND

Reluctance to Use Artificial Intelligence

While billions of dollars have been invested in AI development, adoption of AI-based systems has been slower than expected, which is not surprising. Even before the emergence of AI, consumers tended to show resistance to technological innovations (Kleijnen, Lee, and Wetzels 2009, Ram and Sheth 1989). One major barrier to the adoption of innovations is perceived risk as they are inherent in new innovations (Laukkanen 2016, Mahmud, Islam, and Mitra 2023, Ram and Sheth 1989). Indeed, prior research has shown that consumers are reluctant to adopt predictions or recommendations made by AI-based systems compared to those made by comparable humans in domains ranging from healthcare to forecasting.

This reluctance is driven by unique beliefs or expectations about AI (Castelo, Bos, and Lehmann 2019, Dietvorst, Simmons, and Massey 2015, Longoni, Bonezzi, and Morewedge 2019, Önkal et al. 2009, Promberger and Baron 2006). First, consumers believe that algorithms lack fundamental human traits, such as emotional abilities, which lowers their perceived efficacy. For example, for subjective (vs. objective) tasks, such as seeking dating advice, algorithms are considered less effective because they lack emotional capabilities (Castelo, Bos, and Lehmann 2019). This perceived lack of personal feelings or empathy also lowers purchases when people interact with an AI chatbot (Luo et al. 2019). Additionally, the belief that algorithms lack the ability to adapt to various unexpected cases leads to an aversion to using AI healthcare providers (Longoni, Bonezzi, and Morewedge 2019).

Second, consumers treat errors or mistakes made by algorithms more severely. Algorithms are expected to achieve perfect accuracy in forecasting tasks, so when they err, consumers are more likely to abandon them (Dietvorst, Simmons, and Massey 2015). Consumers also believe that algorithms are less capable of learning from mistakes than humans (Reich, Kaju, and Maglio 2023). Third, when things do go awry, consumers find it more difficult to assign responsibilities for outcomes to algorithms than to humans (Önkal et al. 2009, Promberger and Baron 2006).

Taken together, prior research has primarily compared algorithms with comparable human providers and has shown why consumers are hesitant to use algorithms, a phenomenon coined "algorithm aversion" (Dietvorst, Simmons, and Massey 2015). One recent exception examines consumer preference by distinguishing between low- and high-adaptivity algorithms (Clegg et al. 2024). This study shows that the greater the extent to which algorithms can adjust their operations independently of a programmer (i.e., high adaptivity), the more it is perceived as creative but less predictable. However, previous research has mainly focused on output quality or effectiveness, such as how well algorithms perform tasks in the ways consumers expect them to. We extend this line of research in the context of services operated by conversational AI systems, focusing on consumers' fundamental perceptions of such systems, which may occur prior to evaluating the systems' performance. How do consumers respond to AI systems that augment their capabilities by learning about them?

Aversion of Being a Test Subject

As society, technology, and culture have evolved, so too has human learning; in many ways, the two have a symbiotic relationship, propelling each other (Greenfield 2009, Wootton 2015). While many methods of human learning exist, experimentation is typically considered a foundational component of modern scientific learning dating back to the 17th century (Dear 2016, Gross and Krohn 2005). Humans have always been the observer, leveraging experiments as a tool to learn, but they have also frequently been observed as an experimental subject particularly in psychology, other social sciences, and business (Bromley et al. 2015, Luca 2014, Oakley 2000, Zoumpoulis, Simester, and Evgeniou 2015). This has been done by other humans and under the protective eyes of the law; for example, federally mandated institutions, such as institutional review boards (IRBs), protect the rights and safety of research participants. As such, the term “subject” is no longer considered appropriate as it carries a connotation that the respondent is a passive entity who can be unfairly taken advantage of (Bromley et al. 2015). We use this term here to draw attention to this aspect. Admittedly, outside the realm of academia, such as in corporate experiments, ethical considerations are sometimes not as strictly addressed as they are in academia (Luca 2014). People often view experiments conducted by organizations as less appropriate (Heck et al. 2020; Meyer et al. 2019). Nonetheless, there are specific parties involved in these experiments as well as outside ones where people can take actions to address their discomfort if they may experience.

In recent times, we have seen the birth of a new observer, AI, which can also learn from us. Humans are not the only entities capable of expanding their knowledge base and growing; AI systems do so as well. Currently, AIs do not conduct experiments but learn using unique methods. They learn from datasets and enhance their performance autonomously without human intervention. Humans learn from experiments by gathering data about subjects’ behaviors and from their responses, which they analyze, and draw conclusions from. The AI learning process also starts with data collection from users, which is then analyzed using advanced mathematical and statistical models, to derive output. Both types of learning occur based on identified patterns or relationships in the data.

While experimentation with human observers has evolved over centuries, experimentation using AI observers is novel, and has limited rules. Consequently, human respondents are uncertain about how their data will be utilized and what will happen to their information after AI has learned from them. The machine learning process is likely to be seen as a black box (Pasquale 2015). Even with increasing education about AI, designing and understanding algorithms is a specialized skill, inaccessible to the general public (Burrell 2016). In other words, the average consumer often has difficulty understanding what exact process their information goes through to train algorithms and the ultimate purpose of its learning. Advancing ethical research involving human subjects involves making the research process more transparent to participants, such as by using informed consent and debriefing (NCPHSBBR 1979, Lahman 2018).

Subjects of the AI systems, on the other hand, are less likely to have a comprehensive understanding of how AI deep learning works, such as what their information will be turned into through learning, and how it will affect them. While some systems notify users at the outset that they do not store personal data and do not share this with third parties, the questions relating to what deep learning will reveal about subjects and other potential consequences of deep learning about them remain unanswered.

AI Exploitation

We propose that consumers believe it is riskier to use algorithms that learn from them (vs. do not). These beliefs are an outcrop of feelings of being exploited. It is well known that people want equitable exchanges and feel duped when one gives more than one has received (Vohs, Baumeister, and Chin 2007). While these feelings primarily arise in exchanges between individuals, they can also be triggered in exchanges between a human and a human artifact, such as a machine or a computer (Vohs, Baumeister, and Chin 2007). We believe that consumers are likely to perceive having their data used for algorithm learning as an unfair exchange. With human subjects, researchers are required to assess risks and benefits associated with a study—risks to participants are expected to be minimized and be reasonable in comparison to potential benefits (NCPHSBBR 1979, Lahman 2018). We expect subjects to also assess risks and benefits when they are asked to provide their personal information while interacting with AI systems. However, the potential risks stemming from AI's learning processes are completely unknown. Thus, we believe that AI learning algorithms might evoke a sense of being exploited among its users.

One might primarily attribute feelings of exploitation to privacy concerns. While privacy is a complex concept that comprises of different elements, a key aspect involves an individual's ability to control their information including how it is shared and who has access to it (Culnan and Armstrong 1999, Martin and Murphy 2017, Smith, Dinev, and Xu 2011, Solove 2011). Consequently, people feel their privacy is invaded when unauthorized access occurs due to a security breach or when their personal information, provided for one purpose, is used for unrelated secondary purposes, such as for marketing (Culnan and Armstrong 1999, Smith, Milberg, and Burke 1996). Admittedly, interacting with AI systems inevitably leads to the disclosure of personal information and people are concerned about their information privacy (Easwara Moorthy and Vu 2015, Lim and Shim 2022). Indeed, even if an AI system has completed its learning process, it still needs users' personal information for processing, which we believe will invoke privacy concerns.

While we expect privacy concerns to remain important when subjects use AI systems, there may be additional unique mechanisms that underlie aversion to interacting with "learning" algorithms. What are consumers most concerned about when it comes to deep learning AI? Are they just concerned with releasing their information and how and with whom it is shared? Fortunately, many companies are stringent about protecting consumers' data privacy. For instance, ChatGPT assures users that their data will be protected and not sold for other irrelevant marketing purposes. Would this policy then address concerns consumers have regarding "learning" algorithms? We do not believe so. While we agree that any data that consumers provide will evoke privacy concerns because of the potential for unauthorized use (e.g., for marketing processes) and/or security breaches (e.g., information hacks and data breaches), learning systems also evoke a different set of concerns—a piece of information provided by a consumer may turn into an encyclopedia on them.

AI systems comprise of three elements: data collection and storage, computational techniques, and output systems (Puntoni et al. 2021). These three elements empower the system to carry out tasks for consumers. Learning for AI is an iterative process, where it continuously refines its knowledge base through training on new data. Thus, as more data becomes available for learning, AI systems can dynamically adjust their understanding in response to new data (Kühl et al. 2022). Consequently, the specific pieces of information provided directly to the system are not just stored in a static manner; they are integrated into an evolving knowledge base. Thus, the concerns with AI learning are less about consumers' data being readily made available to unauthorized entities or being used for unrelated purposes—after all the data were provided in the context of an existing relationship and had not been leaked or stolen; but relates more to how consumers' data will be transformed into knowledge as a result of learning.

We propose that AI's deep learning about oneself can invoke three types of concerns. First, consumers may be concerned about harm from the knowledge that AI's deep learning acquires about them. For example, it may learn things that consumers do not want to reveal, which could be used to draw accurate or erroneous inferences or be used against them in the future. The two other factors are related to the beneficiaries of this learning. While the system does provide consumers with valuable personalized services currently, the service quality is likely to be even better in the future, as the algorithm is likely to improve through deep learning using the subject's data. Two groups of people can benefit from this—future customers and the company. Future customers can derive direct benefit from the enhanced quality of service. This can also translate into financial gains for the company.

To summarize, we propose that there are three potential components contributing to consumers' feelings of being exploited—concerns about AI's deeper understanding that might harm oneself in the future, benefits that future customers of the system might derive, and benefits that the company might derive. We test how these three processes play a role in eliciting feelings of exploitation, which subsequently influence the perceived risk of using the AI system in our empirical study.

OVERVIEW OF STUDIES

We test consumers' aversion to becoming test subjects of AI-learning systems across six studies (all studies, except for one, were preregistered), each in a different context. Across all studies except in study 5, the independent variable was whether the AI system is still learning from the provided data to update the system's knowledge base (e.g., algorithms) or has completed the learning process, which we treat as the control condition. This comparison closely reflects real-world situations. For example, ChatGPT provides consumers with the option to not have their data used for training. If consumers opt out, the model generates responses based on the knowledge it was initially trained on up to its last update. In addition, Apple Intelligence (i.e., Apple's large language models including Siri) runs on-device models, thus the output generated by the AI stays on the devices and is not used to train the model (AppleInsider 2024). Although people generally view algorithms as less capable of learning than humans, describing an agent as a machine learning algorithm can enhance consumer trust in its output likely because of the word "learning" (Reich, Kaju, and Maglio 2023). In other words, consumers may broadly assume that AI systems are constantly learning. However, due to the variety of AI models and how they function in the real-world, consumers may be uncertain about how the learning actually occurs—whether the AI continuously learns from every individual interaction, broader user patterns, or if it is even learning at all after deployment.

Across all studies except in study 5, our dependent variable was the perceived risk of using the system. All measures are used on a 7-point scale. In the appendix, we provide all the stimuli and measures used in each study.

Study 1 provides an initial understanding of how consumers perceive AI-based systems that are learning. Some might argue that when AI systems are still learning, it suggests further development is needed, making people reluctant to use what they perceive as an incomplete system. We investigate whether learning AI systems are perceived to provide fewer benefits to consumers or pose a greater risk of using the system. Studies 2A and 2B provide initial evidence of our effect. Studies 3 and 4 delve deeper into delineating the factors that drive the feelings of exploitation. In study 3, we show that feelings of exploitation are not solely an outcrop of privacy concerns—along with privacy concerns, participants are uncomfortable with the idea that their data is used as training data to improve the AI model. Building upon the findings from study 3, in study 4 we explored the specific concerns consumers have regarding using their data for AI learning. We test three elements that could contribute to the feelings of being exploited caused by AI learning: concerns that AI's deeper understanding might (1) harm them in the future (future harm), (2) benefit future customers of the system (future customers' benefit), and (3) benefit the company (company's benefit). In study 5, we examine an intervention for firms to promote AI-powered services with learning models while mitigating the concerns of potential harm—not retaining any personally identifiable user details in the system. In study 6, we examine the downstream consequences (6A) and behavioral outcomes (6B) of data sharing depending on whether AI-based systems are learning or not. Together, the findings show that consumers are concerned about being exploited by AI which affects their perceptions of AI use. For a summary, see Table 1.

TABLE 1

SUMMARY OF EMPIRICAL STUDIES

Study	Sample	Context	Dependent Variables	Completed learning	Continuous learning
1	MTurk N = 307	Financial consultation system	Perceived benefit Perceived risk	4.46 (1.31) 3.76 (1.55)	4.56 (1.44) 4.43 (1.65)
2A	MTurk N = 268	Financial consultation system	Perceived risk	3.66 (1.48)	4.53 (1.59)
2B	Prolific N = 266	Health consultation system	Perceived risk	3.60 (1.51)	3.87 (1.58)
3	MTurk N = 349	Dating system	Perceived risk	3.86 (1.71)	4.65 (1.60)
4A	Prolific N = 362	Life coaching system	Perceived risk	3.41 (1.58)	4.32 (1.60)
4B	MTurk N = 355	Travel guidance system	Perceived risk	2.94 (1.39)	3.76 (1.48)
5	Prolific N = 539	Mind therapy system	Perceived risk	3.74 (1.52)	4.35 (1.65) 3.60 (1.57)
6A	MTurk N = 438	Financial consultation system	The level of detail people are willing to share	4.51 (1.73)	4.04 (1.78)
6B	Connect N = 165	Life supporting system	The number of words provided	62.58 (39.17)	56.35 (39.07)

STUDY 1

The goal of study 1 is to gain initial insights into consumers' perceptions of AI systems that learn from interactions with users. People typically trust human professionals who have completed their learning and are maybe certified more than those who are still in training. Unlike in the human world, ironically, AI systems' continuous learning can be seen in a positive light as it suggests that the AI system is improving and will be more helpful and can accord greater benefits to consumers. Concurrently, because this learning occurs due to real-time interactions with users it can also be concerning. Thus, it is unclear if assumptions that one makes about expertise among humans can translate to AI systems. Indeed, consumers often assess the benefits and risks of using technological tools when asked to provide their personal information during interactions (Chellappa and Sin 2005, Smith, Dinev, and Xu 2011). They trade their information in return for the outcomes they receive. We expect that consumers will perceive no difference in the benefits conferred by AI systems regardless of whether the systems are still updating their algorithms or have completed updating their algorithms. However, we believe that consumers perceive a greater risk of using AI systems that are still learning (vs. control). This study was preregistered (https://aspredicted.org/r5cj-994p).

Participants, Method, and Design

Following our preregistration, we posted 300 slots to recruit US MTurk participants through CloudResearch, and 324 participants enrolled, and all of them completed our study (48.8% female; 79.9% White; M_{age} = 44.7). We administered one attention check question to assess scenario understanding. Participants learned about an AI-based financial consultation system called FinanceBOT. They were asked which of the following statements is correct about FinanceBOT in a multiple-choice question. As preregistered, we excluded participants who failed to answer this question correctly. A final sample of 307 remained (49.8% female; 80.5% White; M_{age} = 45.0).

Participants read about an AI-based financial consultation system, FinanceBOT, which helps people make financial investment decisions after interactive conversations with them. All participants learned that they will be asked to input their personal information such as current financial situation to receive customized recommendations. While we had informed them that

FinanceBOT would ask for this information, we did not collect this information. We then randomly assigned participants to either the control or learning condition After reading the scenario, participants were asked to indicate their perceived benefits of using the system ("How much benefit would you expect to derive by using FinanceBOT?") on a 7-point scale (1 = not much benefit at all to 7 = a lot of benefit) and perceived risk of using the system ("How risky would it be to use FinanceBOT?") on a 7-point scale (1 = not risky at all to 7 = very risky). The order of these two questions was randomized across participants. Finally, we asked participants to provide demographic information including gender, age, and race.

Results and Discussion

As predicted, participants in the learning condition judged the risk of using the FinanceBOT to be greater (n = 162, M = 4.43, SD = 1.65) than those in the control condition (n = 145, M = 3.76, SD = 1.55; F(1, 305) = 13.50, $p < .001$, $\eta_p^2 = .042$). However, the perceived benefits conferred by the FinanceBOT did not differ based on whether the system is learning (M = 4.56, SD = 1.44) or has completed its learning (M = 4.46, SD = 1.31; F(1, 305) = .35, $p = .554$, $\eta_p^2 = .001$).

This study shows that the benefits that participants expect to derive from the AI systems do not differ based on whether the systems are still learning or not. Importantly, the learning AI system (vs. control) poses a greater perceived risk of using the system. This study serves as the foundation for our main hypothesis, which focuses on the increased risk of using the system, rather than decreased benefits derived from learning AI systems. Thus, perceived risk will be the primary focus in subsequent studies. In the next studies, we will delve into the process underlying the elevated risk associated with the use of learning AI systems.

STUDY 2

The goal of studies 2A and 2B is to replicate prior findings of perceived risk and provide the mediating role of feelings of exploitation. These studies were preregistered (2A: https://aspredicted.org/NWR_L62, 2B: https://aspredicted.org/YHJ_MBV).

Participants, Method, and Design

In study 2A, following our preregistration, we posted 300 slots to recruit US MTurk participants through CloudResearch, and 302 participants enrolled in our study (45.4% female; 79.1% White; M_{age} = 42.9). We administered one attention check question to assess scenario understanding. Like the prior study, participants learned about an AI-based financial consultation system called FinanceBOT. They were asked which of the following statements is correct about FinanceBOT in a multiple-choice question. As preregistered, we excluded participants who failed to answer this question correctly. A final sample of 268 remained (44.8% female; 78.4% White; M_{age} = 43.7).

We followed the same procedure as in the prior study, with one change. After participants indicated the perceived risk of using FinanceBOT, they responded to two questions indicating how exploited they felt in using FinanceBOT ("How comfortable do you feel about the manner in which FinanceBOT is using your information for its learning process?", "How much do you feel being exploited by FinanceBOT for using your information for its learning process?") on a 7-point scale (1 = not comfortable at all/not much at all to 7 = very comfortable/very much). We reverse-coded the first question and created a composite measuring feelings of exploitation. All participants provided demographic information including gender, age, and racial identity.

Study 2B uses a similar design, but in a different domain. Participants read information about HealthAI, an AI-based health consultation system. The system is designed to evaluate people's current health status and provide customized nutrition and lifestyle recommendations. Following our preregistration, we opened 300 slots to recruit US participants on Prolific, and 300 participants enrolled in our study (48.3% female; 78% White; M_{age} = 36.6). As in the previous study, participants were asked to respond to one question to assess their understanding of the information provided. As preregistered, those who failed to answer this question correctly were excluded from the analysis, leaving us with 266 participants (49.2% female; 77.1% White; M_{age} = 36.7). After reading the scenario about HealthAI, participants reported perceived risks and feelings of exploitation using the same items used in study 2A. At the end, they provided demographic information.

Results and Discussion

In study 2A, as predicted, participants in the learning condition judged the risk of using FinanceBOT to be greater (n = 148, M = 4.53, SD = 1.59) than those in the control condition (n = 120, M = 3.66, SD = 1.48; $F(1, 266) = 20.99$, $p < .001$, $\eta_p^2 = .073$). Furthermore, participants in the learning condition felt more exploited by the system (M = 4.42, SD = 1.62) than those in the control condition (M = 3.37, SD = 1.54; $F(1, 266) = 28.82$, $p < .001$, $\eta_p^2 = .098$). We tested the mediating role of exploitation on the perceived risk of using via PROCESS Model 4 with 5,000 bootstrapped samples (Hayes 2013). As expected, the feelings of exploitation mediated the effect of AI learning on the perceived risk of using AI (indirect effect = .74, BootSE = .14, 95% CI = [.467, 1.019]). In study 2B and its follow-up, we replicated these results (see the appendix).

We replicated these findings in study 2B. Although not significant, participants in the learning condition judged the risk of using HealthAI to be greater (n = 146, M = 3.87, SD = 1.58) than those in the control condition (n = 120, M = 3.60, SD = 1.51; $F(1, 264) = 2.00$, $p = .159$, $\eta_p^2 = .008$). Furthermore, participants in the learning condition had a stronger sense of being exploited by the system (M = 3.99, SD = 1.64) than those in the control condition (M = 3.20, SD = 1.47; $F(1, 264) = 16.59$, $p < .001$, $\eta_p^2 = .059$). We also tested the mediating role of exploitation on the perceived risk of using PROCESS Model 4 with 5,000 bootstrapped samples. Consistent with our expectations, the feelings of exploitation mediated the effect of AI learning on the perceived risk of using it (indirect effect = .58, BootSE = .15, 95% CI = [.299, .869]).

Although the effects were consistent with our expectations, the results of perceived risk were not significant. After conducting further analyses, we realized that we did not have enough power to test our effects (we used G*Power to compute the achieved power: Power (1-β err prob) = .309 for a two-tailed test). So, we reran the study using the same pool of respondents from Prolific but with a new batch of respondents and increased the target sample size to 400 (https://aspredicted.org/9TM_7QP). As preregistered, we posted 400 slots to recruit US participants on Prolific. While 404 participants accessed our study, two of them did not complete the study, leaving a total of 402 participants (48.5% female; 81.3% White; $M_{age} = 37.1$). Using the preregistered criteria, a final sample of 351 remained (48.7% female; 81.8% White; $M_{age} = 37.4$). Results show that participants in the learning condition judged the risk of using HealthAI to be greater (n = 199, M = 4.01, SD = 1.58) than those in the control condition (n = 152, M = 3.45, SD = 1.44; $F(1, 349) = 11.52$, $p < .001$, $\eta_p^2 = .032$).Furthermore, participants in the learning condition felt more exploited by the system (M = 4.05, SD = 1.55) than those in the control condition (M = 3.20, SD = 1.50; $F(1, 349) = 26.50$, $p < .001$, $\eta_p^2 = .071$). We also tested the mediating role of exploitation on the perceived risk of using PROCESS Model 4 with 5,000 bootstrapped samples. Consistent with the prior study, feelings of exploitation mediated the effect of AI's learning stage on perceived risk (indirect effect = .60, BootSE = .12, 95% CI = [.363, .843]).

Studies 2A and 2B show that when AI-based systems continue to learn from users to develop their algorithms, participants feel that they could be taken advantage of, which in turn increases the perceived risk of using the system. In the next two studies, we explore the underlying factors of these feelings—examining how privacy concerns contribute to perceived risk (study 3) and identifying specific concerns people have when interacting with the learning AI systems (studies 4A and 4B).

STUDY 3

The goal of study 3 is to delve into the drivers of these feelings of exploitation. We propose that, along with privacy concerns, participants will also feel exploited because their data are used as training data to improve the model. Therefore, we predict that both sets of concerns—privacy concerns and concerns that their data are used as training data—will induce feelings of exploitation. This study was preregistered (https://aspredicted.org/JNG_N4N).

Participants, Method, and Design

Following our preregistration, we posted 400 slots to recruit US MTurk participants through CloudResearch, and 402 participants enrolled in our study (57.5% female; 76.4% White; M_{age} = 40.9). As preregistered, participants were excluded from the analysis if they gave an incorrect answer to an attention check question. A final sample of 349 remained (58.2% female; 77.4% White; M_{age} = 41.8).

Participants read about ConnectAI, an AI-based dating system. As in prior studies, all participants learned that the system would ask them to input some of their information, including lifestyle details. We then randomly assigned participants to one of two conditions, either the control or learning condition. After measuring perceived risk of using the system and feelings of exploitation using the same questions used in prior studies, we measured concerns about ConnectAI storing their data in the system ("I am worried that ConnectAI might store my personal information in its system") and using their data to train the model ("I am worried that ConnectAI might use my personal information to train its model") on 7-point scales (1 = strongly disagree, 7 = strongly agree). Finally, participants provided demographic information.

Results and Discussion

First, participants in the learning condition judged the risk of using ConnectAI to be greater (n = 190, M = 4.65, SD = 1.60) than those in the control condition (n = 159, M = 3.86, SD = 1.71; $F(1, 347) = 19.98$, $p < .001$, $\eta_p^2 = .054$). Second, participants in the learning condition felt more exploited by the system (M = 4.51, SD = 1.58) than those in the control condition (M = 3.71, SD = 1.69; $F(1, 347) = 20.91$, $p < .001$, $\eta_p^2 = .057$). Furthermore, two independent ANOVAs with concerns about saving their data and concerns about using their data for training purposes as dependent variables both elicited a main effect of condition. Participants in the learning condition were more concerned about saving their data (M = 5.43, SD = 1.68) than those in the control condition (M = 4.62, SD = 1.96; $F(1, 347) = 17.21$, $p < .001$, $\eta_p^2 = .047$). A similar pattern emerged for concerns about using the data for training ($M_{learning}$ = 4.98, SD = 1.91

vs. $M_{control} = 4.06$, $SD = 2.09$; $F(1, 347) = 18.46$, $p < .001$, $\eta_p^2 = .051$). We employed the SPSS PROCESS customized model with 5,000 bootstrapped samples to run a parallel-serial mediation analysis. As hypothesized, both pathways were significant: (1) condition → concerns about the system saving the data → feelings of exploitation → perceived risk (indirect effect = .16, BootSE = .05, 95% CI = [.072, .276]); (2) condition → concerns about the system using the data to train its model → feelings of exploitation → perceived risk (indirect effect = .17, BootSE = .06, 95% CI = [.079, .296]).

Study 3 shows that feelings of exploitation are not merely driven by privacy concerns. Interacting with various types of technological tools may inevitably raise privacy concerns, especially when such tools ask one's data to operate the services. Importantly, we find additional unique mechanisms inherent to "learning" AI systems. In the next study, we explore specific concerns that people have when using these systems.

STUDY 4

In studies 4A and 4B, we tested the three potential contributors to feelings of exploitation owing to AI learning: future harm to self, future benefit to others, and benefit to the company. These studies were preregistered (4A: https://aspredicted.org/FYB_SK4, 4B: https://aspredicted.org/49N_W9X).

Participants, Method, and Design

Following our preregistration, we posted 400 slots to recruit US participants on Prolific, and 400 participants enrolled in our study (48.5% female; 78% White; $M_{age} = 37.1$). We included the same attention check question as in previous studies to assess scenario understanding. As preregistered, we excluded participants who failed to respond to this question correctly from the analysis. A final sample of 362 remained (49.2% female; 79% White; M_{age} = 37.5).

Participants read about SupportAI, an AI-based life coaching system, which needed user's personal information to deliver this service. Participants were then randomly assigned to either the control or the learning condition. Next, we measured perceived risk of using SupportAI and feelings of exploitation using the same questions used in prior studies. We then measured the three potential concerns that AI's deep understanding might raise—SupportAI might harm them in the future ("How worried are you that AI's deeper understanding of you might harm you in the future?"), benefit future users ("How worried are you that AI's deeper understanding of you might benefit future users of the system?"), and benefit the company ("How worried are you that AI's deeper understanding of you might benefit the company?"; 1 = not worried at all to 7 = very worried). Finally, participants provided demographic information.

Study 4B uses a similar design, but in a different domain. Following our preregistration, we posted 400 slots to recruit US MTurk participants through CloudResearch, and 401 participants enrolled in our study (51.1% female; 78.8% White; M_{age} = 41.8). Consistent with prior studies and as pre-registered, we only included participants who passed the attention check question in our analysis. This resulted in a final sample of 355 (52.7% female; 77.7% White; M_{age} = 42.4). Participants read about TravelAI, an AI-based travel assistant system. The system assists in planning trips and recommends attractions through interactive conversations with users. The remaining procedures are similar to those used in study 4A.

Results and Discussion

In study 4A, first, participants in the learning condition judged the risk of using SupportAI to be greater ($n = 198$, $M = 4.32$, $SD = 1.60$) than those in the control condition ($n = 164$, $M = 3.41$, $SD = 1.58$; $F(1, 360) = 29.41$, $p < .001$, $\eta_p^2 = .076$). Second, participants in the learning condition felt more exploited by the system ($M = 4.31$, $SD = 1.65$) than those in the control condition ($M = 3.45$, $SD = 1.73$; $F(1, 360) = 22.92$, $p < .001$, $\eta_p^2 = .060$). Furthermore, participants in the learning condition were more concerned about potential future harm ($M = 3.93$, $SD = 1.82$) than those in the control condition ($M = 3.24$, $SD = 1.79$; $F(1, 360) = 13.10$, $p < .001$, $\eta_p^2 = .035$). Though not significant, a similar pattern relating to concerns that AI's deep learning might benefit other users in the future also emerged ($M_{learning} = 3.65$, $SD = 1.68$ vs. $M_{control} = 3.32$, $SD = 1.68$; $F(1, 360) = 3.33$, $p = .069$, $\eta_p^2 = .009$). However, concerns about AI's deep learning benefiting the company did not differ across the two conditions ($p = .293$). We employed the SPSS PROCESS customized models with 5,000 bootstrapped samples to run a parallel-serial mediation analysis. Among the three possible pathways, only one was significant: concerns that AI's deep learning might cause future harm to self (indirect effect = .19, BootSE = .06, 95% CI = [.079, .303]).

Results from study 4B show consistent findings. We replicated prior results. First, participants in the learning condition judged the risk of using TravelAI to be greater ($n = 198$, $M = 3.76$, $SD = 1.48$) than those in the control condition ($n = 157$, $M = 2.94$, $SD = 1.39$; $F(1, 353) = 28.79$, $p < .001$, $\eta_p^2 = .075$). Second, participants in the learning condition felt more exploited by the system ($M = 3.70$, $SD = 1.53$) than those in the control condition ($M = 2.77$, $SD = 1.52$; $F(1, 353) = 32.73$, $p < .001$, $\eta_p^2 = .085$).

However, contrary to the prior study, separate ANOVAs on each of the three concerns elicited from AI's deep learning all revealed a main effect of condition. Participants in the learning condition were more concerned about potential future harm ($M = 3.59$, $SD = 1.77$) than those in the control condition ($M = 2.64$, $SD = 1.63$; $F(1, 353) = 26.85$, $p < .001$, $\eta_p^2 = .071$). Participants in the learning condition were also more concerned about AI's deep learning that might benefit other future users than those in the control condition ($M_{learning} = 3.55$, $SD = 1.77$ vs. $M_{control} = 2.82$, $SD = 1.65$; $F(1, 353) = 15.70$, $p <.001$, $\eta_p^2 = .043$). Lastly, participants in the learning condition were more concerned about AI's deep learning that might benefit the company ($M_{learning} = 4.26$, $SD = 1.86$ vs. $M_{control} = 3.63$, $SD = 2.06$; $F(1, 353) = 9.17$, $p = .003$, $\eta_p^2 = .025$).

We employed the SPSS PROCESS customized model with 5,000 bootstrapped samples to run a parallel-serial mediation analysis. Among the three possible pathways, two were significant: (1) condition → concerns about AI's deep learning that might cause future harm → feelings of exploitation → perceived risk (indirect effect = .23, BootSE = .06, 95% CI = [.128, .356]). (2) condition → concerns about AI's deep learning that might benefit the company → feelings of exploitation → perceived risk (indirect effect = .05, BootSE = .03, 95% CI = [.014, .112]).

We conjecture that the two different contexts used in studies 4A and 4B drive the discrepant results on the second pathway (i.e., company's benefit). Participants might believe that companies offering travel assistance services (study 4B) can benefit more from learning from their customer data than those providing life coaching service (study 4A). In other words, life coaching is more customized and may not elicit the same kinds of benefits to the company as learning about customers' travel preferences and styles. While every individual may have idiosyncratic travel preferences and styles, potential travel itineraries are somewhat limited, and firms can learn a lot from their customers. On the other hand, each individual faces unique challenges and has various life goals. Thus, even with deep learning on customer data, it might not always enhance the service quality for life coaching firms given that each new customer brings their own experiences and challenges.

Taken together, participants were primarily worried about the potential of future harm from AI's learning, which elicited the feelings of being exploited, and subsequently increased the perceived risk of using the AI system. These findings, along with Study 3, suggest that AI's learning systems trigger unique negative feelings compared to typical data collection by companies—consumers may also feel discomfort when companies collect data about their online activities. These negative feelings may stem from two main sources. First, privacy concerns—such as the risk of data leaks or the use of data for other secondary purposes. Second, the perception that companies are profiting from their data. Thus, people may appreciate continuous learning algorithms as long as they don't feel concerned about potential future harm to themselves resulting from the learning. For example, Netflix or YouTube's next watch recommendations may not raise significant concern about future harm as their learning outcomes are quickly visible, understandable, and immediately beneficial to consumers, and are unlikely to have negative future impact.

STUDY 5

The goal of study 5 is to test an intervention to alleviate the perceived risk of using AI systems with learning algorithms. If potential future harm contributes to our results, then not retaining any personally identifiable user details in the system can help mitigate this concern, as even if the AI system can generate an encyclopedia on a customer, they will not be able to associate this with the individual. This study was preregistered (https://aspredicted.org/18B_56G).

Participants, Method, and Design

Following our preregistration, we opened 600 slots to recruit US participants on Prolific, and 601 participants enrolled in our study (48.3% female; 77.9% White; M_{age} = 38.7). We administered the same attention check question as in previous studies. Per pre-registration, we excluded participants who failed to respond to this question correctly from the analysis, resulting in 539 participants (47.5% female; 78.8% White; M_{age} = 39.0).

Participants read about TherapyAI, an AI-based mind therapy system. Next, participants were randomly assigned to one of three conditions, of which two conditions, learning and control, are similar to prior studies. In the intervention condition, participants read the same scenario as those in the learning condition but were additionally informed that the AI system will not retain any personally identifiable information while it continues its learning process. After that, participants indicated their perceived risk of using the system and provided demographic information.

Results and Discussion

An ANOVA with perceived risk revealed a main effect of condition ($F(2, 536) = 11.90$, $p < .001$, $\eta_p^2 = .043$). Planned contrasts showed that participants in the learning condition ($n = 196$, $M = 4.35$, $SD = 1.65$) judged the risk of using TherapyAI to be greater than both those in the control (n = 171, M = 3.74, SD = 1.52; t(536) = 3.68, $p < .001$, d = .385) and intervention conditions (n = 172, M = 3.60, SD = 1.57; t(536) = 4.55, $p < .001$, d = .476). Importantly, the control and the intervention conditions did not differ (t(536) = -.84, $p = .401$, d = -.091).

In this study, we find that the perceived risk of using the system is reduced when the AI system cannot link the learning outcomes to participants by learning from de-identified data. Longoni, Bonezzi, and Morewedge (2019) show that consumers are reluctant to be cared for by healthcare AI providers because they view themselves as unique and different from others, a belief that AI providers cannot fully take care of. Our findings also resonate with this suggesting that the belief in their uniqueness could intensify concerns about being tracked or identified by AI systems in the future. Therefore, informing participants that the learning outcomes are not linked to individuals can alleviate their concerns.

STUDY 6A

The goal of study 6A is to examine the downstream consequence of using the AI-based systems that are learning. We believe that if consumers feel a greater risk of using learning systems (vs. learning completed systems), they are less willing to share their information in detail with the system. In this study, we introduced an AI-based financial consultation system which collects seven pieces of one's financial information, ranging from demographic details to financial risk, to generate customized recommendations. We predict that on average across seven items, people are less willing to share their information with the learning system (vs. learning completed system). Since each piece of information addresses a different aspect of finance, we don't have specific predictions for the magnitude of effect for each individual item. We conduct exploratory analyses on this. This study was preregistered (https://aspredicted.org/28gd-637b).

Participants, Method, and Design

Following our preregistration, we posted 450 slots to recruit US MTurk participants through CloudResearch, and 480 participants enrolled in and all of them completed our study (46.3% female; 82.3% White; M_{age} = 45.0). We administered one attention check question to assess scenario understanding. Participants learned about an AI-based financial consultation system called Fin.AI. They were asked which of the following statements is correct about Fin.AI in a multiple-choice question. As preregistered, we excluded participants who failed to answer this question correctly. A final sample of 438 remained (46.3% female; 82.9% White; M_{age} = 45.5).

Participants read about an AI-based financial consultation system, Fin.AI, which helps people improve their financial health after interactive conversations with them. All participants learned that Fin.AI will ask you to input seven pieces of information to provide meaningful recommendations—these are demographic information, income and employment, expenses, savings, investments, debts and liabilities, and financial risks. We then randomly assigned participants to either the control or learning condition. After reading the scenario, participants were asked to indicate how much detail they are willing to share with Fin.AI for each piece of information (e.g., "How much detail are you willing to share about your monthly income and fluctuations in your earnings?"; all seven questions are provided in the appendix) on a 7-point scale (1 = not much detail at all to 7 = very much detail). At the end, demographics were measured.

Results and Discussion

We take the average of the seven items to serve as our main dependent variable. As predicted, participants in the learning condition are less willing to share their information with Fin.AI (n = 233, M = 4.04, SD = 1.78) than those in the control condition (n = 205, M = 4.51, SD = 1.73; $F(1, 436) = 7.65$, $p = .006$, $\eta_p^2 = .017$). For each item, we summarize the findings in Table 2.

In this study, we examine whether the AI system is learning or not affects consequential information sharing behavior. Across all seven items, except for demographic information, we observe a consistent pattern—consumers are less willing to share their information in detail when the system continues to learn. In the next study, we further investigate this behavior by asking people to actually provide their information to the system.

TABLE 2

SUMMARY OF STUDY 6A OUTPUT

Questions	Learning (n = 233)	Control (n = 205)	Statistic
Demographic	M = 4.73 SD = 1.89	M = 4.91 SD = 1.88	$F(1, 436) = 1.02$ $p = .313$, $\eta_p^2 = .002$
Income and employment	M = 3.91 SD = 1.97	M = 4.40 SD = 1.92	$F(1, 436) = 6.77$ $p = .01$, $\eta_p^2 = .015$
Expenses	M = 4.05 SD = 1.91	M = 4.59 SD = 1.86	$F(1, 436) = 8.76$ $p = .003$, $\eta_p^2 = .020$
Savings	M = 4.15 SD = 1.98	M = 4.60 SD = 1.90	$F(1, 436) = 5.98$ $p = .015$, $\eta_p^2 = .014$
Investments	M = 3.71 SD = 2.07	M = 4.24 SD = 1.98	$F(1, 436) = 7.50$ $p = .006$, $\eta_p^2 = .017$
Debt and liabilities	M = 3.82 SD = 2.07	M = 4.30 SD = 2.05	$F(1, 436) = 5.86$ $p = .016$, $\eta_p^2 = .013$
Financial risks	M = 3.92 SD = 1.97	M = 4.52 SD = 1.87	$F(1, 436) = 10.42$ $p = .001$, $\eta_p^2 = .023$

STUDY 6B

Building on findings from the prior study, we aim to examine the behavioral consequences of using the AI-based systems that are learning. Our prior findings show that people are less willing to share their information in detail when AI systems continue to learn (vs. have completed learning). If this is the case, then when we ask people to actually share their information, we should find less information being provided when the AI systems are learning. We test how the number of words differs based on whether the AI system is learning (vs. has completed learning).

Participants, Method, and Design

We posted 200 slots to recruit US participants through Connect, and 201 participants enrolled in our study (44.3% female; 75.6% White; M_{age} = 39.5). We administered one attention check question to assess scenario understanding. Participants learned about an AI-based life supporting system called ThriveAI. They were asked which of the following statements is correct about ThriveAI in a multiple-choice question. As preregistered, we excluded participants who failed to answer this question correctly. A final sample of 165 remained (44.2% female; 75.2% White; M_{age} = 40.3).

Participants read about an AI-based life supporting system, ThriveAI, which helps people achieve their desired goals in all areas of their lives after interactive conversations with them. All participants learned that this application is currently under pilot testing with a small group of users before launching. We then randomly assigned participants to either the control or learning condition. Participants in the learning (vs. control) condition were presented with the application advertisement including a service description that ThriveAI is continuously learning (vs. has completed its learning) to update their knowledge base. Next, we asked them to share details about their current situations, including their goals and anticipated challenges, as well as personal information such as their personality and lifestyle, if they are interested in trying the service and receiving customized guidance. Participants were presented with one open-ended question, and they were able to proceed to the next page without responding to the question. After providing demographic data, they were debriefed before the study ends.

Results and Discussion

We used LIWC (Linguistic Inquiry and Word Count) to count the words that participants provided, which serve as our dependent variable. We analyzed the data using Poisson regression. As predicted, participants in the learning condition provided a smaller number of words (n = 98, M = 56.35, SD = 39.07) than those in the control condition (n = 67, M = 62.58, SD = 39.17; B = -.105, SE = .02, χ^2 (1) = 26.25, *p* <.001).

The results of this study reinforce the findings from the prior study and again confirm our predictions with a consequential behavior measure. We show that when the AI system is still learning (vs. has completed its learning), participants are less likely to share detailed information about themselves, which is reflected in the fewer number of words they provided.

GENERAL DISCUSSION

AI services or platforms powered by deep learning algorithms are revolutionizing various fields ranging from healthcare to education and are bringing dramatic changes to our daily lives. While AI learning algorithms bestow many advantages, including providing more accurate and personalized solutions, consumers are still reluctant to use them—they consider such systems riskier to interact with. In a series of experiments, we show that AI systems that continue to learn are perceived as riskier to use. In study 1, we assessed how benefits and risk of using the learning AI systems are perceived. In studies 2A and 2B, we showed that the increased risk of using the system emerges because people feel exploited by the system. In studies 3, 4A and 4B, we delved into feelings or exploitation by examining the role of privacy concerns and three potential contributors. Study 5 provided one effective intervention to reduce perceived risk associated with learning AI system. In study 6, we investigated the downstream and behavioral consequences of sharing information with learning AI systems. Across a variety of contexts where interactive AI systems are used, we find a robust effect documenting that consumers judged AI systems that are still learning to be riskier to use compared to systems that are not learning.

Theoretical Contributions

Our research helps provide a better understanding of consumer reactions to AI-powered services that use machine learning. Our research contributes to the literature on artificial intelligence (or algorithm) aversion (Castelo, Bos, and Lehmann 2019, Dietvorst, Simmons, and Massey 2015, Longoni, Bonezzi, and Morewedge 2019, Luo et al, 2019, Önkal et al. 2009, Promberger and Baron 2006). Prior studies have shown various beliefs about AI systems ranging from the system's lack of emotional capabilities to their ability to learn from mistakes, compared to humans. We extend this stream of research by focusing on AI systems but by considering the impact of perhaps its most central feature—its ability to learn and improve from a sequence of data. Furthermore, our research shows people's fundamental reticence to use AI systems with learning models. In study 1, we demonstrated that while perceived benefits are not expected to differ regardless of whether the system is still learning or not, participants perceive a greater risk of using the learning system. This suggests that the aversion to using learning AI systems goes beyond concerns about performance and the quality of outcomes it delivers when adopting technology (Ram and Sheth 1989). Our findings are also relevant to a particularly concerning aspect of machine learning—its lack of transparency (Puntoni et al. 2021, Schmidt, Biessmann, and Teubner 2020). We deepen the understanding of the negative consequences of this aspect of

AI by showing people's fear it could lead to lasting harm through continuous algorithm development.

Our findings also contribute to the literature on information privacy (Culnan and Armstrong 1999, Martin and Murphy 2017, Smith, Dinev, and Xu 2011). Prior literature has identified privacy concerns as one deterrent for personal information disclosure (Martin, Borah, and Palmatier 2017, Martin and Murphy 2017). We show that while privacy concerns remain important (e.g., in study 3), interacting with AI systems that use learning models evoke unique additional concerns. These concerns go beyond just data security issues or unauthorized use and expand to concerns about how AI learning can harm consumers in the future.

Managerial Contributions

Our research has also important implications for companies offering services powered by learning algorithms. The size of the global conversational AI market is expected to reach approximately $86.42 billion by 2032 (Zoting 2023). Many systems use a combination of machine learning algorithms, deep learning models, or NLP (natural language processing) techniques to create natural human-computer interactions. Our research documents a critical barrier to AI adoption. Consumers perceive AI systems that learn as riskier to use because they believe the system may take advantage of them in the future. Changing consumers' beliefs, that they are service recipients and not test subjects, would increase consumer usage, which could help companies and the society as a whole harness the full potential of AI and continual technology development.

Our research also suggests the need to develop policies or regulations concerning AI systems that use learning models. The notion of privacy has received attention since the 19th century to safeguard one’s properties (Solove 2004) and privacy concerns became more pronounced with the advancement of the internet and digital technologies. We find that privacy issues are not the sole factors that threat users when using increasingly complex AI systems. Our findings underscore the necessity of actions taken by society at large to alleviate discomfort of users and effectively integrate AI technologies.

We also document an effective intervention that companies can consider. Study 5 shows that the perceived risk of using the system is reduced when AI systems continue to learn from de-identified data. This implies that companies should take steps to alleviate concerns consumers have about the potential consequences of learning. One way to achieve this could be to ensure that personally identifiable information is not stored, as we did in study 5. There may be other approaches firms could use. For example, allowing users to choose what information they want to share for algorithm training could potentially attenuate concerns. Companies could also consider ways to provide benefits that offset the risk of being learned. We leave this for future research.

Limitations and Future Research Directions

Our research opens avenues for future research. In this study, we provide robust evidence for consumers’ resistance to learning algorithms across various contexts. We believe that there are several factors that could serve as boundaries to this effect. For instance, people might perceive less risk in using AI systems if the outcomes of learning have no direct impact on critical aspects of themselves. For example, if the systems are designed to make routine or tedious tasks more convenient, consumers might be less concerned about future harm driven by learning AI. On the other hand, if people believe that the learning outcomes bring clear benefits to them in the future beyond immediate personalized recommendation from the system, their concerns about future harm can be compensated.

Additionally, it is possible that concerns about future harm might be reduced if learning is necessary to contribute to public benefits or society as a whole. For instance, public healthcare centers often need to research people's data to study diseases and develop treatments. In similar to this approach, if the purposes of AI's learning are clear and benefit society, which they contribute to, their aversion to using learning AI systems could be reduced.

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APPENDIX A: STIMULI AND MATERIALS FOR STUDIES IN CHAPTER 2

Preliminary study

We are interested in understanding people's judgements regarding financial decisions. Specifically, we aim to explore how people make decisions about credit card repayments. Please read the following scenario and answer some questions.

[Current Strategy Condition]
Imagine a customer who recently missed making their monthly credit card payment.

Per the credit card company's policy, the customer will be charged a late fee of $29. Along with this, an Annual Percentage Interest Rate (APR) of 24.74% will be levied on the unpaid balance.

The interest fee will be calculated based on the number of days the amount is past due. The interest fees will increase as the number of days the bill is overdue increases.

[Additional Grace Period Condition]
Imagine a customer who recently missed making their monthly credit card payment.

Per the credit card company's policy, the customer will be given 5 days during which no penalties will be levied. After 5 days, the customer will be charged a late fee of $29. Along with this, an Annual Percentage Interest Rate (APR) of 24.74% will be levied on the unpaid balance.

The interest fee will be calculated based on the number of days the amount is past due. The interest fees will increase as the number of days the bill is overdue increases.

- [Current] Given that the customer has been charged a $29 late fee and an APR of 24.74% will be levied on the unpaid balance on a daily basis, how likely is the customer to make a payment right now? (1 = Not likely at all, 9 = Very likely)
- [Add'l.grace.prd.] Given that the customer has been given 5 days during which no penalties will be charged, how likely is the customer to make a payment right now? (1 = Not likely at all, 9 = Very likely)
- How much of their debt will the customer repay? 0% means that they will not repay anything, 100% means that they will repay in full [Slider bar: 0% to 100%]
- How quickly do you think the customer will pay off the outstanding debt? (1 = Not quickly at all, 9 = Very quickly)

- Do you currently own a credit card? (Yes, I do own a credit card; No, I don't own a credit card)
- How well do you understand the manner in which the credit card interest rates work? (1 = Not well at all, 9 = Very well)
- What is your gender? (Male, Female, Non-binary/third gender, Prefer not to say)

- What is your age?

******Note:* We used the same items to measure payment history and credit card usage frequency across all studies. Except for study 1 and 3A, which used a 7-point scale, all other studies used a 9-point scale presented as study 2.

Study 1

Suppose you own a few credit cards. You used your credit cards last month. One of your credit cards had a higher bill than usual. It is $524.

Your budget is really tight this month. If you stretch your money, you could potentially pay the whole amount of this credit card's bill. But you will have to pay very close attention to your spending.

You receive the following email from the credit card company.

[Control Condition]
Dear customer,

I am writing to you to let you know that your balance with us is now overdue.
In addition to interest charges on the unpaid balance, we also charge a $35 late fee. You will see these charges in your statement.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

[Additional Grace Period Condition]
Dear customer,

I am writing to you to let you know that your balance with us is now overdue.
In addition to interest charges on the unpaid balance, we also charge a $35 late fee.

However, we offer a grace period of ONE WEEK. If you pay within this week, you will NOT incur interest charges and will NOT have to pay the $35 late fee. You will not see these charges in your statement.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

- How much of your $524 credit card bill will you pay now? (Remember this does NOT include the $35 late fee) [Slider bar: $0 to $524]

- Please answer this question based on the scenario provided. Do you have to pay the late fee if you pay your bill now? (Yes, I have to pay the late fee; No, I do not have to pay the late fee)

- What is your gender? (Male, Female, Non-binary/third gender, Prefer not to say)
- What is your age?
- How often do you use credit cards? (1 = Not often at all, 7 = Very often)
- To what extent do you agree or disagree with the following? (1 = Strongly disagree, 7 = Strongly agree)
    - I always pay my credit card balance off in full each month.
    - I often make only minimum payment on my credit card bills.

Study 2

Suppose you own a few credit cards. You used your credit cards last month. One of your credit cards had a higher bill than usual. It is $604.

Your budget is really tight this month. If you stretch your money, you could potentially pay the whole amount of this credit card's bill. But you will have to pay very close attention to your spending.

You receive the following email from the credit card company.

[Control Condition]
Dear customer,

I am writing to you to let you know that your balance with us is now overdue.
In addition to interest charges on the unpaid balance, we also charge a $29 late fee. You will see these charges in your statement.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

[Additional Grace Period Condition]
Dear customer,

I am writing to you to let you know that your balance with us is now overdue.
In addition to interest charges on the unpaid balance, we also charge a $29 late fee.
However, we offer a 4-day grace period. If you pay within this period, you will NOT incur interest charges and will NOT have to pay the $29 late fee. You will not see these charges in your statement.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

[Not Missed Payment Condition]
Dear customer,

I am writing to you to let you know that your balance with us is now at 4 days remaining.
If you do not pay within the next 4 days, in addition to interest charges on the unpaid balance, we will also charge a $29 late fee.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

- [Control] How much of your $604 credit card bill will you pay now? (Remember this does NOT include the $29 late fee) [Slider bar: $0 to $604]
- [Add'l.grace.prd. & Not missed payment] How much of your $604 credit card bill will you pay now? [Slider bar: $0 to $604]

- Please answer this question based on the scenario provided. Do you have to pay the late fee if you pay your bill now? (Yes, I have to pay the late fee; No, I do not have to pay the late fee)

- To what extent do you agree or disagree with the following? (1 = Strongly disagree, 9 = Strongly agree)
  - I always pay my credit card balance off in full each month.
  - I often make only minimum payment on my credit card bills.
- What is your gender? (Male, Female, Non-binary/third gender, Prefer not to say)
- What is your age?
- How often do you use credit cards? (1 = Not often at all, 9 = Very often)

Study 3A

Same as Study 1 with a change in the credit card balance to $687 and the addition of the following measures:

- How motivated are you to pay off all of your credit card bill now? (1 = Not motivated at all, 9 = Very motivated)

- How much do you believe you have an opportunity to get a fresh start from the next billing cycle? (1 = Not much at all, 9 = Very much)
- How much do you believe you have an opportunity to get a new beginning from the next billing cycle? (1 = Not much at all, 9 = Very much)
- How much do you believe you have an opportunity to clear your past credit card bill? (1 = Not much at all, 9 = Very much)

Study 3B

Same as Study 3A with a change in the credit card balance to $826, a 4-day grace period, and the addition of a measure of reciprocity:

According to the email from the credit card company to what extent do you agree or disagree with the following statements? (1 = Strongly disagree, 9 = Strongly agree)

- I feel like I owe the credit card company.
- I feel like I am indebted to the credit card company.
- I feel like I should reciprocate for what the credit card company has provided for me.

Study 3C

Same as Study 3B, with the measure of reciprocity replaced by anticipated regret.

- How much regret will you feel if you do not pay your credit card bill now? (1 = not much at all, 9 = very much)
- How uncomfortable will you feel if you do not pay your credit card bill now? (1 = not uncomfortable at all, 9 = very uncomfortable)
- How bad will you feel if you do not pay your credit card bill now? (1 = not bad at all, 9 = very bad)

Study 3D

[Control Condition] As your balance is now overdue, in addition to interest charges on the unpaid balance, we also charge a $27 late fee.

[Additional Grace Period Condition] As your balance is now overdue, in addition to interest charges on the unpaid balance, we also charge a $27 late fee.

However, we offer an additional 4-day grace period—if you pay within this period, you will NOT incur interest charges and will NOT have to pay the $27 late fee. You will not see these charges in your final statement.

[Payment-based Penalty Condition] As your balance is now overdue, in addition to interest charges on the unpaid balance, we also charge a $27 late fee.

However, we offer an additional 4-day grace period—if you pay within this period, your interest charges will be adjusted accordingly based on your payment. In addition, you will NOT incur the $27 late fee. The total charges on your final statement will also be updated based on your payment.

- [Control] How much of your $854 credit card bill will you pay now, apart from any additional charges?
- [Add'l.grace.prd. & Payment-based.] How much of your $854 credit card bill will you pay now?

Study 4A

Suppose you own a few credit cards. You used your credit cards last month. You check your Mastercard's account statement. Your last month's bill is $416. The payment is due within the next 7 days.

Mastercard's Account Summary

Total Balance	$416
Annual Percentage Rate (APR)	21.99%
Late Fee	$29

You also used another credit card, a VISA card. You receive an email from the credit card company.

[Control Condition]
Dear customer,

I am writing to you to let you know that your balance ($409) with us has been overdue for 6 days.

In addition to interest charges on the unpaid balance (19.99% APR), we also charge a late fee ($23). You will see these charges in the next statement.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

[Additional Grace Period Condition]
Dear customer,

I am writing to you to let you know that your balance ($409) with us has been overdue for 6 days.

We offered you an additional 7-day grace period as no payment had been made until the payment due date. If you pay within this period, you will NOT incur interest charges (19.99% APR) and will NOT have to pay the late fee ($23). You will not see these charges in the next statement. Your grace period will expire in 1 day.

You can view and pay your invoice online.
If you have any further questions, you may contact us.

Regards,
Customer support team

After looking at your upcoming month's anticipated expenses, you will have about $700 left over to pay your two credit cards' bills.

[Control Condition]
Below is the summarized information about the two credit cards:

Mastercard Account Summary

- **Payment is due within the next 7 days**

Total Balance	$416
Annual Percentage Rate (APR)	21.99%
Late Fee	$29

VISA Card Account Summary

- **Past due**

Total Balance	$409
Annual Percentage Rate (APR)	19.99%
Late Fee	$23

- Remember you will have about $700 left over to pay your two credit cards' bills. Please indicate the amount of each credit card bill you will pay now (your total should equal to $700).
  - Mastercard ($416) $___
  - VISA card ($409) $___

[Additional Grace Period Condition]
Below is the summarized information about the two credit cards:

Mastercard Account Summary

- **Payment is due within the next 7 days**

Total Balance	$416
Annual Percentage Rate (APR)	21.99%
Late Fee	$29

VISA Card Account Summary

- **Past due**
- **An additional 7-day grace period will expire tomorrow**

Total Balance	$409
Annual Percentage Rate (APR)	19.99%
Late Fee	$23

- Remember you will have about $700 left over to pay your two credit cards' bills. Please indicate the amount of each credit card bill you will pay now (your total should equal to $700).
  - Mastercard ($416) $___
  - VISA card ($409) $___

- Please answer this question based on the scenario provided earlier. According to the email from VISA card, do you have to pay the late fee if you pay your bill now? (Yes, I have to pay the late fee; No, I do not have to pay the late fee)

Same demographic and individual difference measures.

Study 4B

We want to understand how consumers make financial decisions.

You will take part in a Financial Simulation Game where you will have: a financial budget to pay your debt and invest. You can distribute your budget as you wish between paying your debt and investing. However, based on your decisions, you may earn a bonus. We will choose 20 people randomly and pay them the bonus.

We would like to now show you an example:

Initial Budget = $100
You can use this to pay your debt and invest in stock.

Let's say you pay $60 toward your Credit Card Bill.
This implies the remaining amount ($40) will be invested in Stock.
(Initial Budget of $100 - Credit Card Bill of $60 = $40).

If your stock is now worth $80, then your Final Balance = $80.

The question below will test your understanding of this concept. If you answer incorrectly, you will NOT be able to participate in our simulation game. You will have one attempt to get it right.

Initial Budget = $120
You can use this to pay your debt and invest in stock.

- If you pay $40 toward your Credit Card Bill, then how much will be invested in Stock? (Please enter only numbers) _____
- If your stock is now worth $60 then what is your Final Balance? (Please enter only numbers) _____

Finance Simulation Game Starts Now…

Imagine you live in a country that uses a currency called UTY (Ꞓ).

Initial Budget = Ꞓ800.

You can use this money to pay an Overdue credit card bill and/or Invest in the stock market. We will explain this in the subsequent screens.

[Control Condition]

<u>OVERDUE CREDIT CARD BILL</u>
ACCOUNT SUMMARY

- Overdue Amount: Ꞓ600
- Late Fee: Ꞓ20

As the minimum payment (Ꞓ40) has NOT been paid by the due date, you are being charged a late fee and your APR may be increased. Even if you make payments now, these charges will still show up on your next statement.

[Additional Grace Period Condition]

<u>OVERDUE CREDIT CARD BILL</u>
ACCOUNT SUMMARY

- Overdue Amount: Ꞓ600
- Late Fee: Ꞓ20

As the minimum payment (Ꞓ40) has NOT been paid by the due date, you are being charged a late fee and your APR may be increased.

However, you have an Additional 3-day Grace Period: If you make payments within this period, then late fees will not be incurred and your APR will not be increased. These charges will NOT show up on your next statement. Your grace period will expire in 1 day.

STOCK INVESTMENT

You also have the opportunity to invest your money in the stock market. You are considering one stock whose return will be realized next month.

The average return rate is 27%.
For example, on average Ͼ100 investment will become Ͼ127 next month.
Every individual's experience may be different — your return may be higher or lower.

Your task is to allocate your available budget (Ͼ800) towards paying down your credit card bill and/or investing in the stock. After you make your allocation decision, we will randomly select 20 participants and award bonus payments based on final balance.

[Control Condition]
This is the summarized information about your overdue credit card bill and the stock performance:

Credit Card Bill	***Stock***
✓ Overdue Amount Ͼ600 ✓ Late Fee Ͼ20	**Average Return Rate: <u>27%</u>** On average a **Ͼ100** investment will become **Ͼ127** next month. Your return can be <u>higher</u> or <u>lower</u> than 27%.
As the minimum payment (Ͼ40) has NOT been paid by the due date, <u>you are being charged a late fee and your APR may be increased.</u> Even if you make payments now, these charges will **still show up on your next statement.**	

Please indicate how you are going to spend your available budget:

- You need to use up all Ͼ800.
- You are allowed to enter only whole numbers.

Credit card balance (Ͼ600, this does not include the late fee) Ͼ____
Stock Ͼ____

[Additional Grace Period Condition]
This is the summarized information about your overdue credit card bill and the stock performance:

Credit Card Bill	***Stock***
✓ Overdue Amount Ͼ600 ✓ Late Fee Ͼ20 We are reminding you that…. ➢ **Additional 3-day Grace Period** has been applied to your account. ➢ <u>This period will **expire in 1 day**.</u> If you make payments within this period, then late fees will NOT be incurred, and your APR will NOT be increased. These charges will **NOT show up on your next statement.**	**Average Return Rate: <u>27%</u>** On average a **Ͼ100** investment will become **Ͼ127** next month. Your return can be <u>higher</u> or <u>lower</u> than 27%.

Please indicate how you are going to spend your available budget:

- You need to use up all Ͼ800.
- You are allowed to enter only whole numbers.

Credit card balance (Ͼ600) Ͼ____
Stock Ͼ____

Running the Simulation Program…
If you invested in stock, your rate of return is XYZ%

** Below is a screenshot of the example of the final results page presented to participants — every respondent's experience was different as stock returns were drawn randomly from a distribution of returns as described in the paper**

Simulation Game Results:

The amount of money invested in stock: Ͼ200
Rate of return: 29.58%
Total return from stock: Ͼ259.16

The remaining credit card balance after a payment: Ͼ0
Late Fee: Ͼ20

Final Balance at the end of next month: Ͼ239.16

We will randomly select 20 participants and award bonus payments based on the final balance at the end of next month using a conversion rate of Ͼ1 (UTY) = $0.01 (USD).

Your Bonus Payment: $2.39

- Please recall the credit card's policy and answer the following question. If you pay the credit card bill now, will the late fee appear on the statement? (Yes, the late fee will still appear; 2 = No, the late fee will not appear)

Same demographic and individual difference measures, with the addition of a measure of risk-seeking in investment.

- When thinking of your financial investments, how willing are you to take risks? (1 = Not at all willing, 9 = Very willing)

APPENDIX B: FURTHER ANALYSES OF STUDIES IN CHAPTER 2

Preliminary Study Procedures and Results

The goal of this study is to understand how respondents judge the efficacy of providing an additional grace period in promoting repayment among consumers who have missed their credit card payments in comparison to the current practice. This study was preregistered (https://aspredicted.org/64S_XZK).

Participants, Method, and Design

Following our preregistration, we recruited 300 MTurk participants through CloudResearch (45.7% female; M_{age} = 41.80). As preregistered, we included participants who currently possess a credit card in our analysis. A final sample of 267 remained (46.4% female; M_{age} = 41.70). Participants read a short scenario about a customer who missed making their credit card payment. In the current practice condition, the customer would be charged a late fee of $29, and an APR of 24.74% will be applied on the unpaid balance. In the additional grace period condition, the customer was to be given an additional 5-day period during which no fees or fines would be levied. After this period, a late fee of $29, and an APR of 24.74% would be applied on the unpaid balance. In both conditions, participants were also informed that the interest fee would be calculated based on the number of days the amount was past due. In other words, the interest fees would increase along with the number of days the bill was overdue.

Next, we asked respondents three questions. They indicated how likely they thought the customer would make a payment now ("How likely is the customer make a payment right now?"; 1 = not likely at all, 9 = very likely), how much would they repay ("How much of their debt will the customer repay?" on a slider bar 0% = not repaying anything to 100% = repaying in full), and the expected payoff duration ("How quickly do you think the customer will pay off the outstanding debt?"; 1= not quickly at all, 9 = very quickly). After responding to these three questions, participants indicated whether they currently own a credit card or not ("Do you currently own a credit card?"; "Yes, I do own a credit card", "No I don't own a credit card"). We also measured their understanding of how credit card interest rates work ("How well do you understand the manner in which the credit card interest rates work?"; 1 = Not well at all, 9 = Very well). Finally, we measured gender and age.

Results and Discussion

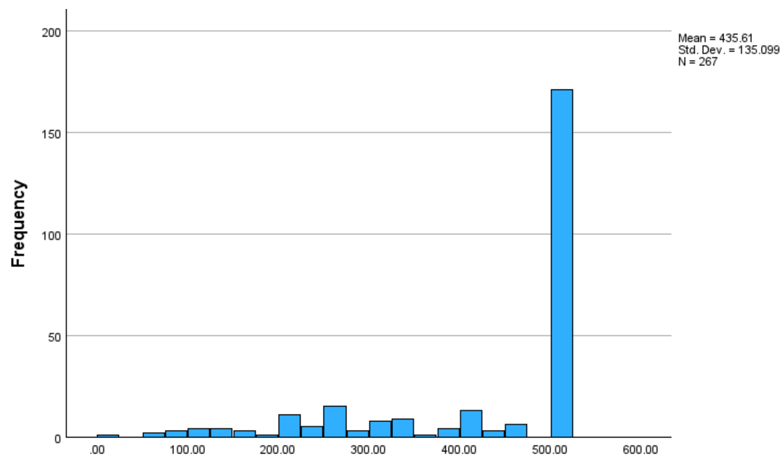
First, participants' comprehension of credit card interest rates did not differ between two groups ($M_{current}$ = 7.22, SD = 1.74, n = 140; $M_{add'l.grace}$ = 7.31, SD = 1.89, n = 127; $F(1,265)$ = .177, p = .674). An ANOVA with the likelihood of making a payment revealed that respondents did not differ in their prediction about the efficacy of the two strategies in eliciting repayments ($M_{current}$ = 6.52, SD = 2.17; $M_{add'l.grace}$ = 6.52, SD = 2.08; $F(1,265)$ = .000, p = .995). Similarly, an ANOVA conducted on the repayment rate also revealed that there was no difference in prediction between the two strategies ($M_{current}$ = 56.91%, SD = 33.90; $M_{add'l.grace}$ = 56.95%, SD = 35.41; F(1,265) = .000, *p* = .991). However, because the Shapiro-Wilk test of normality showed that the distribution of the repayment rate deviated from a normal distribution (skewness = -.10; Shapiro Wilk's W = .90, $p < .001$), we conducted the same analysis again but after applying a square root transformation to the percentage response data. A similar pattern of results emerged ($M_{current}$ = 7.01, SD = 2.80; $M_{add'l.grace}$ = 7.03, SD = 2.75; F(1,265) = .006, *p* = .940). Lastly, an ANOVA with the expected duration for paying off the outstanding debt revealed that there was no difference in prediction between the two strategies ($M_{current}$ = 5.41, SD = 2.53; $M_{add'l.grace}$ = 5.27, SD = 2.56; F(1,265) = .221, *p* = .639).

Discussion. The findings from this preliminary study suggest that when judging the efficacy of these strategies in eliciting repayments from others, respondents do not believe one strategy to be more successful over the other. The null effect observed is likely due to respondents' inability to predict how others would behave—some believe that the "stick" strategy would be more successful while others feel that the "carrot" strategy would be more effective. This is not surprising given that respondents are often unable to assess how others respond in given situations (Weaver et al., 2012). In subsequent studies, we ask respondents to play the role of consumers who have failed to make payments on time, and study how those experiencing the two strategies influence repayment decisions.

Further Analyses of Study 1

Note: We followed the analyses plan and exclusion criteria described in the preregistrations. We indicated in our preregistrations that we would consider different types of tests (e.g., regressions, as well as other parametric and non-parametric tests) to examine our effects based on the distribution of data. The data for one of our dependent measures, amount repaid, consistently violated normality, and was significantly skewed (see each section). We therefore employed non-parametric tests to study differences in amount repaid across the conditions. In addition, we also report results including all respondents instead of ones that passed the preregistered attention check question.

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	$435.61	$135.10
Payment History	5.07	2.00
Frequency of Credit Card Usage	4.81	2.02

Results of Adding Individual Difference Variables

We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from "Non-binary/third gender" and "Prefer not to say" from the gender identity question due to very small sample size in both categories (0.75%). Adding covariates does not meaningfully influence the additional grace period effect (B = 1.03, Wald $\chi^2 = 12.08$, $p < .001$).

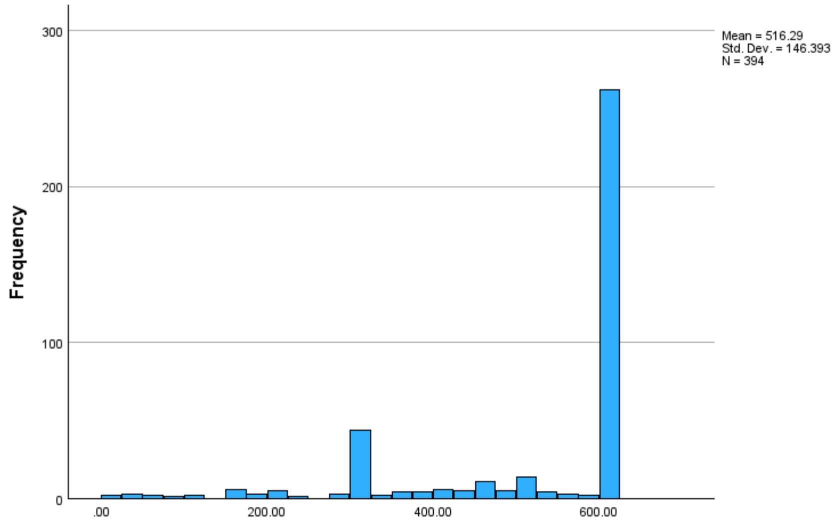
Results from the Full Sample

N = 300	Control (N = 147)	Add'l Grace Period (N = 153)
Full Payment	51.0% (SD = .50)	72.5% (SD = .45)
	B = .93, Wald χ^2 = 14.44, p < .001	
Amount Repaid	$402.50 ($150.39)	$460.65 ($119.41)
	Mann-Whitney U = 8728, z = -3.84, p < .001, r = .22	

Notes: A total of 307 MTurk workers clicked this study, with 7 not completing it, resulting in 300 participants who finished the entire study. Among 307 participants, 153 of them were assigned to the control condition and 154 to the additional grace period condition.

Further Analyses of Study 2

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	\$516.29	\$146.39
Payment History	6.43	2.70
Frequency of Credit Card Usage	6.19	2.64

Results of Adding Individual Difference Variables

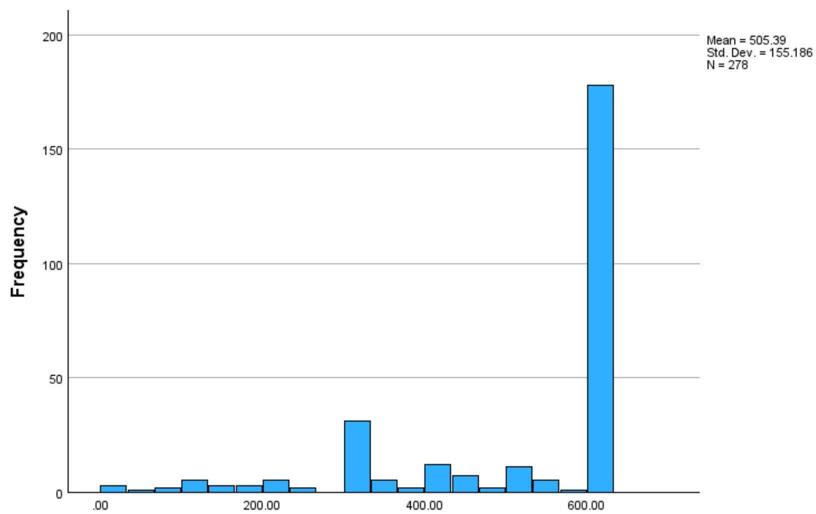
We regressed full payment (1 = full payment, 0 = no full payment) on condition (0 = control, 1 = additional grace period, 2 = not missed), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (3.3%). A binary logistic regression revealed a main effect of condition (Wald $\chi^2 = 29.65$, p <.001). A larger number of participants in the additional grace period group repaid their debt in full relative to those in the missed payment control group (B = 1.60, Wald $\chi^2 = 25.19$, $p < .001$). A larger number of participants in the not missed payment group repaid their debt in full relative to those in the missed payment control group (B = 1.42, Wald $\chi^2 = 20.42$, $p < .001$). Full payment rate did not differ between the not missed payment and the additional grace period groups (B = .17, Wald $\chi^2 = .34$, $p = .562$). Therefore, adding covariates does not meaningfully change the findings reported in the main paper.

Results from the Full Sample

N = 450	Control (N = 148)	Add'l Grace Period (N = 151)	Not missed (N = 151)
Full Payment	54.1% (SD = .50)	70.9% (SD = .46)	68.9% (SD = .46)
	Main effect of condition: Wald χ^2 = 10.85, *p* = .004 Grace - Control: B = .73, Wald χ^2 = 8.89, *p* = .003 Not missed - Control: B = .63, Wald χ^2 = 6.87, *p* = .009 Grace - Not missed: B = .094, Wald χ^2 = .14, *p* = .707		
Amount Repaid	\$482.97 (\$159.88)	\$520.98 (\$147.45)	\$525.83 (\$141.66)
	Kruskal-Wallis test, H(2) = 9.96, *p* = .007 Grace - Control: Mann-Whitney U = 9433, z = -2.68, *p* = .007, r = .15 Not missed - Control: Mann-Whitney U = 9421.5, z = -2.68, *p* = .007, r = .15 Grace - Not missed: Mann-Whitney U = 11341.5, z = -.096, *p* = .924, r = .01		

Further Analyses of Follow-up to Study 2

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	\$505.39	\$155.19
Payment History	6.54	2.70
Frequency of Credit Card Usage	6.27	2.78

Results of Adding Individual Difference Variables

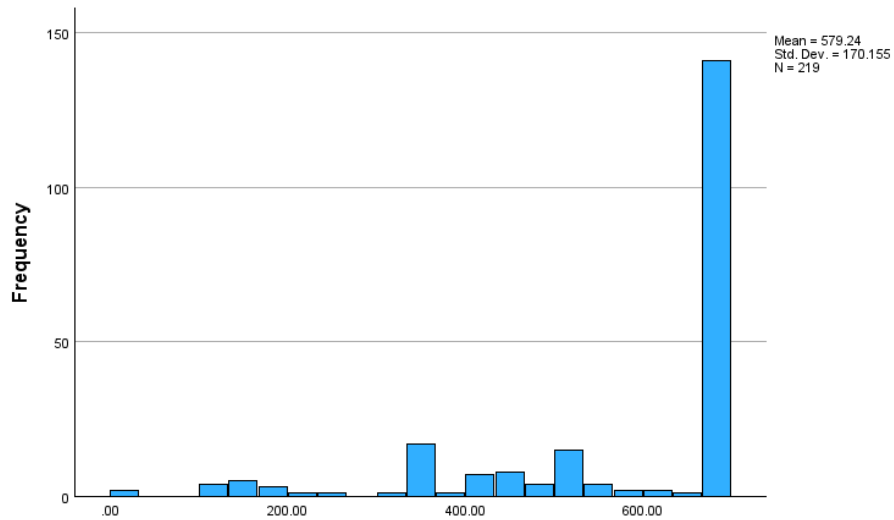
We regressed full payment (1 = full payment, 0 = no full payment) on condition (0 = control, 1 = additional grace period, 2 = not missed), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (1.1%). A binary logistic regression revealed a main effect of condition (Wald $\chi^2 = 11.90$, $p = .003$). A larger number of participants in the additional grace period group repaid their debt in full relative to those in the missed payment control group (B = 1.20, Wald $\chi^2 = 11.28$, $p < .001$). There was no difference in full payment rate between the missed payment control group and the not missed payment group (B = .27, Wald $\chi^2 = .69$, $p = .405$). More participants repaid the full amount in the additional grace period condition than in the not yet missed payment condition (B = .93, Wald $\chi^2 = 6.77$, $p = .009$). Therefore, adding covariates does not meaningfully change the findings reported in the main paper.

Results from the Full Sample

N = 300	**Control (N = 101)**	**Add'l Grace Period (N = 100)**	**Not missed (N = 99)**
Full Payment	57.4% (SD = .50)	75% (SD = .44)	58.6% (SD = .50)
	Main effect of condition: Wald $\chi^2 = 8.18$, $p = .017$ Grace - Control: B = .80, Wald $\chi^2 = 6.81$, $p = .009$ Not missed - Control: B = .048, Wald $\chi^2 = .028$, $p = .868$ Grace - Not missed: B = .75, Wald $\chi^2 = 5.95$, $p = .015$		
Amount Repaid	\$484.65 (\$163.96)	\$537.74 (\$135.73)	\$490.40 (\$162.05)
	Kruskal-Wallis test, H(2) = 8.38, $p = .015$ Grace ~ Control: Mann-Whitney U = 4130, z = -2.65, $p = .008$, r = .19 Not missed - Control: Mann-Whitney U = 4923.5, z = -.21, $p = .836$, r = .01 Grace - Not missed: Mann-Whitney U = 4109, z = -2.47, $p = .013$, r = .18		

Further Analyses of Study 3A

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	$579.24	$170.15
Motivation	7.87	1.82
Measure of Fresh Start	7.15	2.05
Payment History	5.24	1.82
Frequency of Credit Card Usage	4.65	2.16

Results of Adding Individual Difference Variables

We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (2.28%). Adding covariates does not meaningfully influence the grace period effect (B = .66, Wald $\chi^2 = 4.52$, p = .033). We also performed a regression analysis on motivation using the same predictors. Results revealed that a main effect for condition still emerges (B = .53, t(212) = 2.20, p = .029).

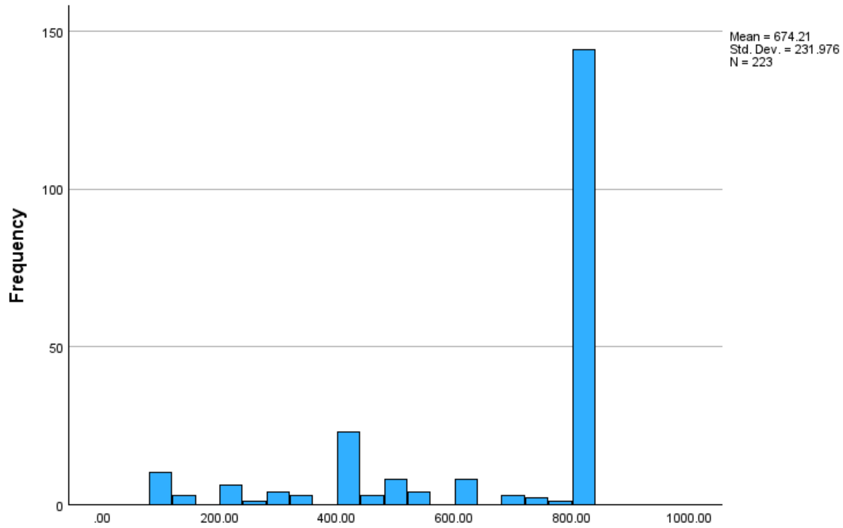
Results from the Full Sample

N = 250	Control (N = 120)	Add'l Grace Period (N = 130)
Full Payment	56.7% (SD = .50)	69.2% (SD = .46)
	B = .54, Wald $\chi^2 = 4.20$, $p = .04$	
Amount Repaid	$555.68 ($181.28)	$590.85 ($165.96)
	Mann-Whitney U = 6870.50, z = -1.88, $p = .06$, r = .12	
Motivation	7.58 (2.03)	8.04 (1.67)
	$F(1, 248) = 3.77$, $p = .053$, $\eta_p^2 = .015$	
Fresh Start	6.71 (2.18)	7.45 (1.84)
	$F(1, 248) = 8.58$, $p = .004$, $\eta_p^2 = .033$	
Mediation Analysis	Full Payment: indirect effect = .43, BootSE = .18, 95% CI = [.134, .836] Motivation: indirect effect = .34, BootSE = .13, 95% CI = [.101, .624] Serial Mediation (condition – fresh start – motivation – full payment): indirect effect = .69, BootSE = .34, 95% CI = [.209, 1.504]	

Notes: A total of 262 MTurk workers clicked this study, with 12 not completing it, resulting in 250 participants who finished the entire study. Among 262 participants, 130 of them were assigned to the control condition and 130 to the additional grace period condition. Two participants were not assigned to any condition.

Further Analyses of Study 3B

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	$674.21	$231.98
Motivation	7.49	2.27
Measure of Fresh Start	6.81	2.11
Measure of Reciprocity	6.32	2.13
Payment History	6.30	2.86
Frequency of Credit Card Usage	6.42	2.62

Results of Adding Individual Difference Variables

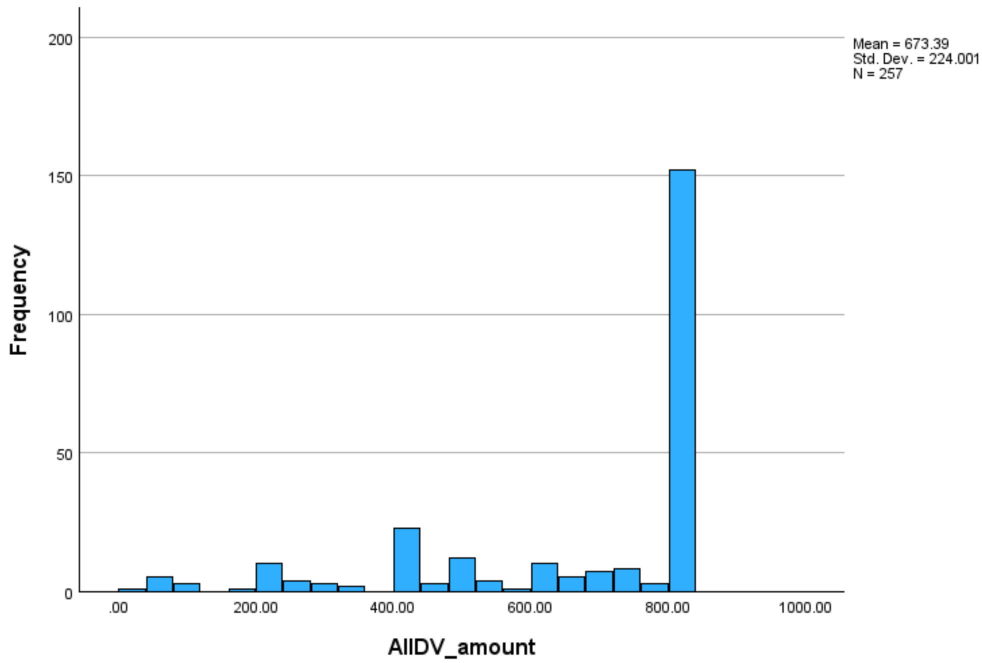
We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (3.14%). Adding covariates does not meaningfully influence the grace period effect (B = .72, Wald $\chi^2 = 4.59$, p = .032). We also performed a regression analysis on motivation using the same predictors. Results revealed that a main effect for condition still emerges (B = .48, t(216) = 1.74, p = .083).

Results from the Full Sample

N = 251	Control (N = 125)	Add'l Grace Period (N = 126)
Full Payment	60% (SD = .49)	69% (SD = .46)
	B = .40, Wald χ^2 = 2.24, p = .135	
Amount Repaid	\$660.70 (\$229.48)	\$688.42 (\$229.87)
	Mann-Whitney U = 7238.5, z = -1.29, p =.196, r = .08	
Motivation	7.30 (2.41)	7.78 (1.98)
	F(1, 249) = 3.00, p = .084, η_p^2 = .012	
Fresh Start	6.43 (2.17)	7.20 (1.93)
	F(1, 249) = 8.95, p = .003, η_p^2 = .035	
Mediation Analysis	Full Payment: indirect effect = .41, BootSE = .16, 95% CI = [.143, .759] Motivation: indirect effect = .40, BootSE = .15, 95% CI = [.124, .718] Serial Mediation (condition – fresh start – motivation – full payment): indirect effect = .53, BootSE = .25, 95% CI = [.172, 1.162]	

Further Analyses of Study 3C

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	$673.39	$224.00
Motivation	7.92	1.75
Measure of Fresh Start	7.01	1.88
Measure of Anticipated Regret	7.04	2.10
Payment History	6.15	2.57
Frequency of Credit Card Usage	6.23	2.58

Results of Adding Individual Difference Variables

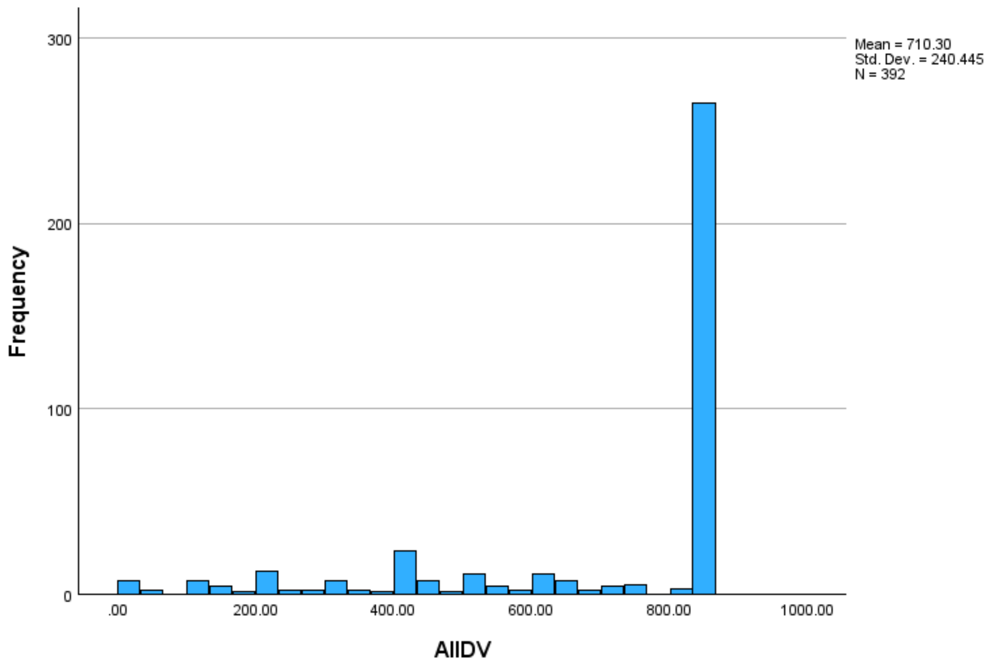
We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from "Non-binary/third gender" and "Prefer not to say" from the gender identity question due to very small sample size in both categories (1.6%). Adding covariates does not meaningfully influence the additional grace period effect (B = 1.29, Wald χ^2 = 18.48, $p < .001$). We also performed a regression analysis on motivation using the same predictors. Results revealed that a main effect for condition still emerges (B = .48, $t(250) = 2.36$, $p = .019$).

Results from the Full Sample

N = 300	Control (N = 149)	Add'l Grace Period (N = 151)
Full Payment	49% (SD = .50)	64.2% (SD = .48)
	B = .63, Wald χ^2 = 7.04, *p* = .008	
Amount Repaid	$634.56 ($233.38)	$692.17 ($218.19)
	Mann-Whitney U = 9546.5, z = -2.51, *p* =.012, r = .14	
Motivation	7.45 (2.22)	7.99 (1.60)
	F(1, 298) = 5.93, *p* = .015, η_p^2 = .020	
Fresh Start	6.71 (1.99)	7.20 (1.72)
	F(1, 298) = 5.33, *p* = .022, η_p^2 = .018	
Mediation Analysis	Full Payment: indirect effect = .20, BootSE = .10, 95% CI = [.027, .433] Motivation: indirect effect = .26, BootSE = .13, 95% CI = [.042, .536] Serial Mediation (condition – fresh start – motivation – full payment): indirect effect = .20, BootSE = .12, 95% CI = [.029, .477]	

Further Analyses of Study 3D

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	$710.30	$240.44
Payment History	6.18	2.58
Frequency of Credit Card Usage	5.90	2.65

Results of Adding Individual Difference Variables

We regressed full payment (1 = full payment, 0 = no full payment) on condition (0 = control, 1 = additional grace period, 2 = payment-based grace period), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (0.8%). A binary logistic regression revealed a main effect of condition (Wald $\chi^2 = 8.80$, $p = .012$). A larger number of participants in the additional grace period group repaid their debt in full relative to those in the control group (B = .81, Wald $\chi^2 = 7.97$, $p = .005$). A larger number of participants in the payment-based grace period repaid their debt in full relative to those in the control group (B = .65, Wald $\chi^2 = 5.21$, $p = .022$). Full payment rate did not differ between the additional and payment-based grace period (B = .16, Wald $\chi^2 = .35$, $p = .555$).

Therefore, adding covariates does not meaningfully change the findings reported in the main paper.

Results from the Full Sample

N = 300	Control (N = 148)	Add'l Grace Period (N = 151)	Payment-based (N = 151)
Full Payment	58.1% (SD = .50)	70.2% (SD = .46)	66.9% (SD = .47)
	Main effect of condition: Wald χ^2 = 5.09, p = .078 Grace - Control: B = .53, Wald χ^2 = 4.72, p = .030 P.B - Control: B = .38, Wald χ^2 = 2.45, p = .117 Grace – P.B: B = .15, Wald χ^2 = .38, p = .536		
Amount Repaid	$685.68 ($237.58)	$715.79 ($241.50)	$697.44 ($258.81)
	Kruskal-Wallis test, H(2) = 3.06, p = .217 Grace - Control: Mann-Whitney U = 10057, z = -1.74, p =.081, r = .10 P.B - Control: Mann-Whitney U = 10516.5, z = -1.01, p = .311, r = .06 Grace – P.B: Mann-Whitney U = 10974, z = -.68, p = .495, r = .04		

Ruling Out Other Alternative Explanations—Study 3E

We consider the following alternate explanations other than a sense of reciprocity: perceptions of task urgency, importance, and feelings of regret. First it is possible that offering an additional grace period might simply make debt repayment salient because of which consumers may judge repaying the overdue debt as an urgent or an important task that should be undertaken immediately. Previous research suggests that task urgency triggers psychological tension increasing propensity to act on the task (Zhu et al., 2018). However, in our contexts, the task is equally urgent and important in both conditions—after all, both groups of consumers missed making a credit card payment. Furthermore, while urgency or importance can increase willingness to make a payment immediately, it is unclear why it would increase the amount repaid. Another possible explanation could be that the additional grace period evoked feelings of regret. The additional grace period was after all provided because consumers failed to make the initial payment, so it could engender greater regret. Regretful consumers may make greater debt repayments to improve their current circumstance as a way of correcting their past failures (Roese & Summerville, 2005; Zeelenberg, 1999), which could explain the additional grace period effect. Accordingly, we subject this to empirical testing.

In this study, we measured the proposed underlying mechanism and three potential alternative explanations to test whether the effect is driven by the belief of getting a fresh start. The study thus uses a single factor design with two between-subjects conditions: an additional grace period and a control condition. The study was preregistered (https://aspredicted.org/MJP_RNW).

Participants, Method, and Design

We recruited 250 participants through MTurk (53.6% female; M_{age} = 41.80). We included the same attention check item as in previous studies. As preregistered, participants who failed to pass this question were excluded from analysis, leaving us with 221 participants (52.5% female; M_{age} = 42.05).

We employed a study design similar to the one used in the previous study with a few differences. We changed the amount due to $826 and we reduced the additional grace period to 4 days. Except for the additional information provided in the additional grace period condition, all participants read the same information. Participants then indicated how much of their credit card bill they would pay now (“How much of your $826 credit card bill will you pay now?”), and how motivated they are to repay the entire credit card bill (“How motivated are you to pay off all of your credit card bill now?”; 1= not motivated at all, 9 = very motivated).

Next, we measured beliefs about starting afresh using the same three questions that we used in studies 3, which we combined together (Cronbach’s alpha = .928). We then measured importance (“How important do you think it is to pay your credit card bill now?”; 1 = not important at all, 9 = very important), urgency (“How urgent do you think it is to pay your credit card bill now?”; 1 = not urgent at all, 9 = very urgent), and regret (“How regretful do you feel about not paying your credit card bill on time?”; 1 = not regretful at all, 9 = very regretful).

Finally, as in our previous studies, participants indicated their payment history with two items (Cronbach's alpha = .753) along with gender, age, and frequency of credit card use.

Results and Discussion

Full Payment. A binary logistic regression revealed that more people repaid the full amount in the additional grace period condition (n = 120; 73.3%, SD = .44) than in the control condition (n = 101; 47.5%, SD = .50; B = 1.11, Wald χ^2 = 14.99, p < .001).

Amount Repaid. Because the distribution of the amount repaid was skewed (skewness = -1.12; Shapiro-Wilk's W = .80, p < .001), we used a nonparametric test. Consistent with our previous findings, participants in the additional grace period condition repaid more of their debt (M = $709.73, SD = $212.86) than those in the control condition (M = $610.99, SD = $248.68; Mann-Whitney U = 4561.5, z = -3.61, p < .001, r = -24).

Motivation to pay off debt. Consistent with study 2A findings, an ANOVA with motivation to pay off debt elicited a main effect of condition (F(1, 219) = 17.61, p < .001, η_p^2 = .074). Participants in the additional grace period (M = 8.02, SD = 1.70) were more motivated to clear their past bill than in the control condition (M = 6.80, SD = 2.57).

Fresh start. An ANOVA with fresh start elicited a main effect of condition (F(1, 219) = 24.99, p < .001, η_p^2 = .102). Participants were more likely to believe that they would have an opportunity to start anew in the additional grace period condition (M = 7.54, SD = 1.56) than in the control condition (M = 6.29, SD = 2.15).

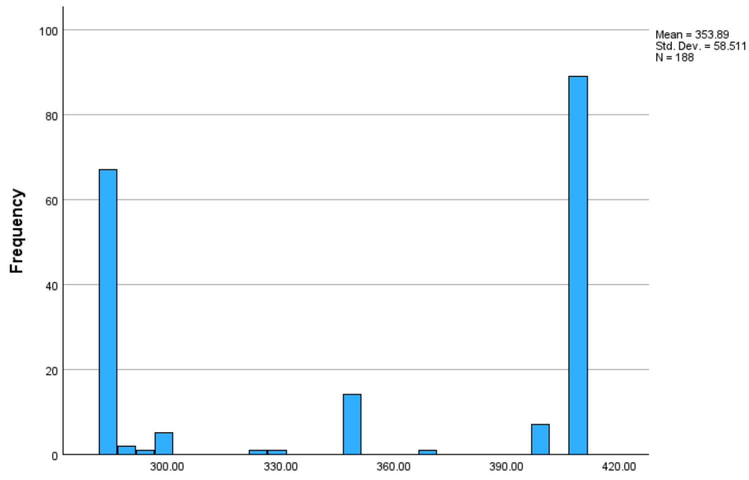
Mediation Analysis. We conducted a mediation analysis using PROCESS (Model 4, number of bootstrap samples: 5000, Hayes 2013) to test the role of beliefs about starting afresh in impacting the additional grace period effect. Consistent with the prior findings, the path from condition (additional grace period vs. control) to full payment was significantly mediated by beliefs of starting afresh (indirect effect = .89, BootSE = .24, 95% CI = [.506, 1.448]). The direct effect from condition to the proportion who repaid the full amount was however no longer significant (direct effect = .52, SE = .34, z = 1.51, p = .131). A similar mediation analysis with motivation led to similar results. Motivation to clear past debt was significantly mediated by beliefs of starting afresh (indirect effect =.88, BootSE = .21, 95% CI = [.506, 1.317]). The direct path from condition to motivation was no longer significant (direct effect = .33, SE = .24, t = 1.37, p = .171). While we did not include a serial mediation analysis in our preregistration, we conducted one (model 6 with 5,000 bootstrap samples); condition (additional grace period vs. control) as the independent variable, full payment rate as the dependent variable, and an opportunity to start afresh and motivation to pay off debt as two serial mediators in this sequence. The results reveal that the serial mediation was significant (indirect effect = 1.28, BootSE = .42, 95% CI = [.668, 2.340]). The mediation via an opportunity to start afresh alone was not significant.

Alternative Explanations. We conducted several different analyses to rule out alternative explanations. We first conducted an ANOVA with importance of paying the credit card bill as the dependent variable and condition as the independent variable. Perceived importance did not differ between the two conditions ($M_{add'l.grace}$ = 8.04, SD = 1.51 vs. $M_{control}$ = 7.79, SD = 1.67; $F(1, 219) = 1.36$, $p = .245$, $\eta_p^2 = .006$). A similar analysis with urgency of paying the credit card bill also did not elicit any differences ($M_{add'l.grace}$ = 7.79, SD = 1.61 vs. $M_{control}$ = 7.56, SD = 1.81; $F(1, 219) =.97$, $p = .325$, $\eta_p^2 = .004$).

A similar analysis with regret, however, elicited a main effect of condition ($F(1, 219) = 4.30$, $p = .039$, $\eta_p^2 = .019$). However, the pattern of effects was counter to what we might have expected. Participants felt more regret in the control condition ($M_{add'l.grace}$ = 7.18, SD = 2.16 vs. $M_{control}$ = 7.74, SD = 1.86). Thus, feelings of regret also cannot explain the additional grace period effect.

Further Analyses of Study 4A

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid (Visa)	$353.89	$58.51
Amount Repaid (Master)	$346.11	$58.51
Payment History	6.61	2.53
Frequency of Credit Card Usage	6.52	2.66

Results of Adding Individual Difference Variables

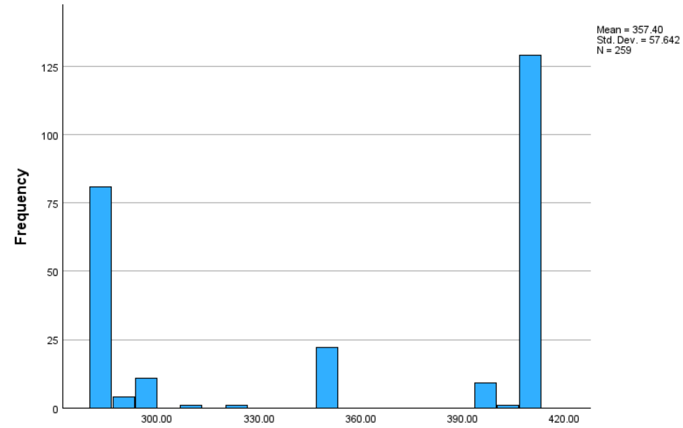
We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from "Non-binary/third gender" and "Prefer not to say" from the gender identity question due to very small sample size in both categories (1.06%). Adding covariates does not meaningfully influence the grace period effect (B = .53, Wald χ^2 = 2.93, p = .087).

Results from the Full Sample

N = 200	Control (N = 99)	Add'l Grace Period (N = 101)
Full Payment	43.4% (SD = .50)	53.5% (SD = .50)
	B = .40, Wald χ^2 = 2.01, p = .157	
Amount Repaid	$349.90 ($58.67)	$360.70 ($57.51)
	Mann-Whitney U = 4489.5, z = -1.35, p = .175, r = .10	

Further Analyses of Follow-up to Study 4A

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid (Visa)	\$357.40	\$57.64
Amount Repaid (Master)	\$342.60	\$57.64
Payment History	6.70	2.53
Frequency of Credit Card Usage	6.15	2.63

Results of Adding Individual Difference Variables

We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from the gender identity question due to very small sample size in both categories (2.32%). Adding covariates does not meaningfully influence the grace period effect (B = 1.02, Wald $\chi^2 = 15.26$, $p < .001$).

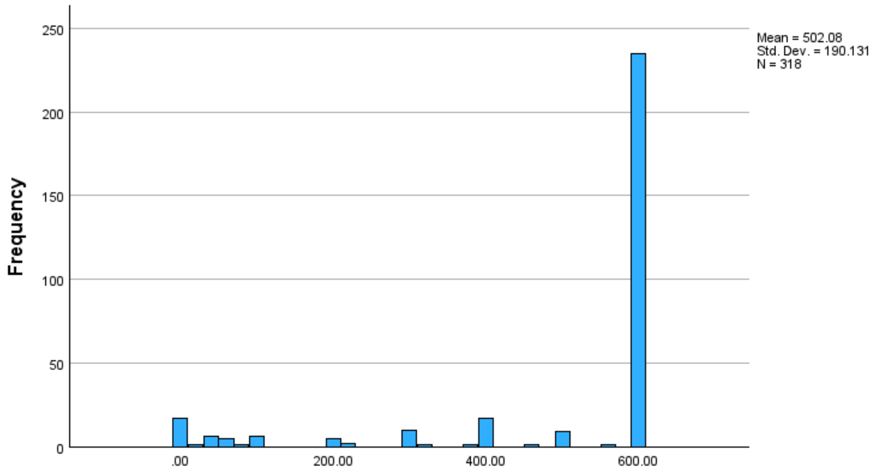
Results from the Full Sample

N = 301	**Control (N = 147)**	**Add'l Grace Period (N = 154)**
Full Payment	37.4% (SD = .49)	58.4% (SD = .49)
	B = .86, Wald $\chi^2 = 13.12$, $p < .001$	
Amount Repaid	\$343.54 (\$57.67)	\$368.52 (\$54.49)
	Mann-Whitney U = 8533.5, z = -3.99, $p < .001$, r = .23	

Notes: A total of 311 MTurk workers clicked this study, with 10 not completing it, resulting in 301 participants who finished the entire study. Among 311 participants, 156 of them were assigned to the control condition and 154 to the additional grace period condition. One participant was not assigned to any condition.

Further Analyses of Study 4B

Data Distribution



Descriptive Statistics

Variable	Mean	SD
Amount Repaid	\$502.08	\$190.13
Amount Invest	\$297.92	\$190.13
Investment Risk	4.61	2.10
Payment History	6.55	2.73
Frequency of Credit Card Usage	6.22	2.68

Results of Adding Individual Difference Variables

We regressed full payment (1 = full payment, 0 = no full payment) on condition (1 = additional grace period, 0 = control), gender, age, frequency of using credit cards, willingness to take investment risk, and payment history. We combined responses from “Non-binary/third gender” and “Prefer not to say” from a gender identity question due to very small sample size in both categories (0.63%). Adding covariates does not meaningfully influence the grace period effect (B = .48, Wald $\chi^2 = 3.26$, $p = .071$).

Results from the Full Sample

N = 350	Control (N = 175)	Add'l Grace Period (N = 175)
Full Payment	68.0% (SD = .47)	77.1% (SD = .42)
	B = .46, Wald $\chi^2 = 3.65$, $p = .056$	
Amount Repaid	\$489.66 (\$192.72)	\$508.74(\$189.43)
	Mann-Whitney U = 14124, z = -1.60, $p = .11$, r = .09	

Appendix References

Roese, Neal J., and Amy Summerville (2005), “What We Regret Most... and Why,” *Personality and Social Psychology Bulletin*, 31 (9), 1273-1285.

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APPENDIX C: STIMULI AND MATERIALS FOR STUDIES IN CHAPTER 3

Study 1

FinanceBOT is an AI based financial consultation system. The system will help you make financial investment decisions through interactive conversations with you.

FinanceBOT will ask you to input your personal information including investment goals and will give you customized recommendations based on this. It will also help you make these investments.

----Next page----
FinanceBOT has learned from thousands of people's personal situations and financial decision-making. Based on this knowledge, FinanceBOT can provide you with optimal financial recommendations.

FinanceBOT will ask you to input the following information:
- Current Age
- Retirement Age
- Current financial situation (income and expenditure)
- Investment goal (maximize short term gains vs. long term gains)

----Next page----
[Control] As it has COMPLETED its algorithm development, FinanceBOT will NOT USE your information to update its knowledge base. In other words, your information will NOT be utilized as training data for its learning process.

[Learning] As it CONTINUES to develop its algorithm, FinanceBOT will USE your information to update its knowledge base. In other words, your information will also be UTILIZED as training data for its learning process.

----Next page----
- How risky would it be to use FinanceBOT? (1 = not risky at all, 7 = very risky)
- How much benefit would you expect to derive by using FinanceBOT? (1 = not much benefit at all, 7 = a lot of benefit)

----Next page----

Please answer this question based on the scenario that you read earlier:

- Which of the following statements is correct?
    - FinanceBOT will UTILIZE your information as training data to update its algorithms.
    - FinanceBOT will NOT UTILIZE your information as training data to update its algorithms.

----Next page----

- What is your age? (please enter an integer)
- What is your gender? (Male, Female, Non-binary/third gender, Prefer not to say)
- What is your race? (Please select all that apply.)
    - American Indian or Alaska Native
    - Asian
    - Black or African American
    - Native Hawaiian or Pacific Islander
    - White
    - Other (please specify)
    - Prefer not to say

Study 2A

FinanceBOT is an AI based financial consultation system. The system will help you make financial investment decisions through interactive conversations with you.

FinanceBOT will ask you to input your personal information including investment goals and will give you customized recommendations based on this. It will also help you make these investments.

----Next page----

FinanceBOT has learned from thousands of people's personal situations and financial decision-making. Based on this knowledge, FinanceBOT can provide you with optimal financial recommendations.

FinanceBOT will ask you to input the following information:

- Current Age
- Retirement Age
- Current financial situation (income and expenditure)
- Investment goal (maximize short term gains vs. long term gains)

----Next page----

[Control Condition] As it has completed gathering data, FinanceBOT will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, FinanceBOT will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

----Next page----

- How risky would it be to use FinanceBOT? (Not risky at all 1, Very risky 7)

----Next page----

- How comfortable do you feel about the manner in which FinanceBOT is using your information for its learning process? (Not comfortable at all 1, Very comfortable 7)
- How much do you feel being exploited by FinanceBOT for using your information for its learning process? (Not much at all 1, Very much 7)

----Next page----

Please answer this question based on the scenario that you read earlier.

- Which of the following statements is correct about FinanceBOT?
    - Your information will be UTILIZED as training data for its learning process.
    - Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 2B

HealthAI is an AI based health consultation system. The system will help you in evaluating your current health status and will provide nutrition and lifestyle recommendations for improving your health through interactive conversations with you.

HealthAI will ask you to input your personal information including current dietary habits, lifestyle details, and medical history and will give you customized recommendations based on these.

----Next page----
HealthAI has learned from thousands of people's personal information and their risk of developing certain diseases. Based on this knowledge, HealthAI can assist you by providing optimal recommendations to improve your health.

HealthAI will ask you to input the following information:
- Demographic information
- Dietary habits
- Current health status
- Lifestyle details
- Medical history (e.g., medication, surgeries, etc.)
- Family medical history

----Next page----
[Control Condition] As it has completed gathering data, HealthAI will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, HealthAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

----Next page----

- How risky would it be to use HealthAI? (Not risky at all 1, Very risky 7)

----Next page----

- How comfortable do you feel about the manner in which HealthAI is using your information for its learning process? (Not comfortable at all 1, Very comfortable 7)
- How much do you feel being exploited by HealthAI for using your information for its learning process? (Not much at all 1, Very much 7)

----Next page----

Please answer this question based on the scenario that you read earlier.

- Which of the following statements is correct about HealthAI?
    - Your information will be UTILIZED as training data for its learning process.
    - Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 3

ConnectAI is an AI based dating system. The system will provide recommendations for potential matches through interactive conversations with you.

ConnectAI will ask you to input your personal information including personality traits and relationship goals and will give you customized partner recommendations based on these.

----Next page----
ConnectAI has learned from thousands of people's personal information and their decisions about potential partners. Based on this knowledge, ConnectAI can provide you with optimal match recommendations.

ConnectAI will ask you to input the following information:
- Demographic information
- Lifestyle details
- Personality traits
- Personal values
- Relationship goals

----Next page----
[Control Condition] As it has completed gathering data, ConnectAI will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, ConnectAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

----Next page----
- How risky would it be to use ConnectAI? (Not risky at all 1, Very risky 7)

----Next page----
- How comfortable do you feel about the manner in which ConnectAI is using your information for its learning process? (Not comfortable at all 1, Very comfortable 7)
- How much do you feel being exploited by ConnectAI for using your information for its learning process? (Not much at all 1, Very much 7)

----Next page----

To what extent do you agree or disagree with the following statements? (Strongly disagree 1, Strongly agree 7)

- I am worried that ConnectAI might store my personal information in its system.
- I am worried that ConnectAI might use my personal information to train its model.

----Next page----

- Which of the following statements is correct about ConnectAI?
  - Your information will be UTILIZED as training data for its learning process.
  - Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 4A

Imagine that you've recently decided to make positive changes in some aspects of your life. You find SupportAI, an AI based life coaching system.

----Next page----

SupportAI will help guide you to achieve your desired goals in all areas or your life ranging from your career to your personal relationships through interactive conversations with you.

SupportAI will ask you to input your personal information including your current emotional status, challenges, and specific goals and will give you personalized guidance and support based on these.

----Next page----

SupportAI has learned from thousands of people's personal information and how they tackle their goals. Based on this knowledge, SupportAI can provide you with customized guidance.

SupportAI will ask you to input the following information:

- Demographic information
- Personal background
- Strengths and weaknesses
- Current emotional status
- Current challenges
- Specific goals that you wish to achieve

----Next page----

[Control Condition] As it has completed gathering data, SupportAI will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, SupportAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

----Next page----

- How risky would it be to use SupportAI? (Not risky at all 1, Very risky 7)

----Next page----

- How comfortable do you feel about the manner in which SupportAI is using your information for its learning process? (Not comfortable at all 1, Very comfortable 7)
- How much do you feel being exploited by SupportAI for using your information for its learning process? (Not much at all 1, Very much 7)

----Next page----

How worried are you that AI's deeper understanding of you…

- might harm you in the future? (Not worried at all 1, Very worried 7)
- might benefit future users of the system? (Not worried at all 1, Very worried 7)
- might benefit the company? (Not worried at all 1, Very worried 7)

----Next page----

- Which of the following statements is correct about SupportAI?
    - Your information will be UTILIZED as training data for its learning process.
    - Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 4B

Imagine that you've recently been thinking about going traveling. You find TravelAI, an AI based travel assistant system.

----Next page----
TravelAI will assist you in planning trips. It helps you book flights and accommodations and recommends attractions that you may wish to visit through interactive conversations with you.

TravelAI will ask you to input your personal information including basic travel information and travel style and will give you personalized travel itinerary based on these.

----Next page----
TravelAI has learned from thousands of people's personal information and their decisions about travel plans. Based on this knowledge, TravelAI can provide you with customized recommendations for your trip.

TravelAI will ask you to input the following information:
- Demographic information
- Basic travel information (e.g., approximate travel dates, budget, and travel companions)
- Travel style
- Past travel experience
- Interests and preferences

----Next page----
[Control Condition] As it has completed gathering data, TravelAI will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, TravelAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

----Next page----
- How risky would it be to use TravelAI? (Not risky at all 1, Very risky 7)

----Next page----
- How comfortable do you feel about the manner in which TravelAI is using your information for its learning process? (Not comfortable at all 1, Very comfortable 7)
- How much do you feel being exploited by TravelAI for using your information for its learning process? (Not much at all 1, Very much 7)

----Next page----

How worried are you that AI's deeper understanding of you…

- might harm you in the future? (Not worried at all 1, Very worried 7)
- might benefit future users of the system? (Not worried at all 1, Very worried 7)
- might benefit the company? (Not worried at all 1, Very worried 7)

----Next page----

- Which of the following statements is correct about TravelAI?
    - o Your information will be UTILIZED as training data for its learning process.
    - o Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 5

Imagine that you've recently decided to improve your mental and emotional well-being.
You find TherapyAI, an AI based mind therapy system.

----Next page----
TherapyAI has learned from thousands of people's personal information and how they improve their mental health. Based on this knowledge, it can provide you with optimal resources.

TherapyAI will help you handle your emotional challenges and provide tools and resources to help you promote your psychological well-being through interactive conversations with you.

----Next page----
TherapyAI will ask you to input your personal information including your personality traits and will give you customized recommendations based on these.

TherapyAI will ask you to input the following information:
- Demographic information
- Lifestyle details
- Personality traits
- Interpersonal relationships
- Life events and changes
- Coping mechanisms and resilience

----Next page----
[Control Condition] As it has completed gathering data, TherapyAI will NOT USE your information to update its knowledge base. Your information will not be utilized as training data for its learning process.

[Learning Condition] As it continues to gather data, TherapyAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

[Intervention Condition] As it continues to gather data, TherapyAI will USE your information to update its knowledge base. Your information will also be utilized as training data for its learning process.

While TherapyAI continues its learning from the information that you provide, any personally identifiable details will not be retained in the system. Your information will only be used as training data for system improvement without retaining any identifiable details, that is, TherapyAI cannot link the data to you.

----Next page----

- How risky would it be to use TherapyAI? (Not risky at all 1, Very risky 7)

----Next page----

- Which of the following statements is correct about TherapyAI?
    - Your information will be UTILIZED as training data for its learning process.
    - Your information will NOT BE UTILIZED as training data for its learning process.

----Next page----

Same demographic questions

Study 6A

Fin.AI is an AI based financial consultation system. The system will help you in effectively managing your finances and will provide recommendations for improving your financial health through interactive conversations with you.
Fin.AI will ask you to input your personal information including income,expenses, debts, and financial risks and will give you customized recommendations based on these.

----Next page----
Fin.AI has learned from thousands of people's personal information and their financial situations. Based on this knowledge, Fin.AI can assist you by providing optimal recommendations to improve your finances.

Fin.AI will ask you to input the following information:
- Demographic information
- Income and employment
- Expenses
- Savings
- Investments
- Debts and liabilities
- Financial risks

----Next page----
[Control Condition] As it has COMPLETED its algorithm developmentFin.AI will NOT USE your information to update its knowledge base. In other words, your information will NOT be utilized as training data for its learning process.

[Learning Condition] As it CONTINUES to develop its algorithm, Fin.AI will USE your information to update its knowledge base. In other words, your information will also be UTILIZED as training data for its learning process.

----Next page----
In order for Fin.AI to provide meaningful recommendations, it needs detailed information about you and your finances. We would like to learn about your willingness to share this information with Fin.AI.

[Control] **As Fin.AI has COMPLETED its algorithm development, it will NOT USE your information to update its knowledge base—your information will NOT be utilized as training data for its learning process.*

[Learning] **As Fin.AI CONTINUES to develop its algorithm, it will USE your information to update its knowledge base—your information will also be UTILIZED as training data for its learning process.*

- How much detail are you willing to share about your demographic information (e.g., gender, age, and race)? (1 = not much detail at all, 7 = very much detail)
- How much detail are you willing to share about your monthly income and fluctuations in your earnings?
- How much detail are you willing to share about your spending habits (e.g., fixed monthly expenses and discretionary spending)?
- How much detail are you willing to share about your saving habits (e.g., amount saved and frequency of saving)?
- How much detail are you willing to share about your investments (e.g., types and amounts)?
- How much detail are you willing to share about your current debts (e.g., credit card debts and loan payments)?
- How much detail are you willing to share about your experience in managing financial risks (e.g., credit, income, or investment risks)?

----Next page----
Please answer this question based on the scenario that you read earlier:

- Which of the following statements is correct?
    - Fin.AI will UTILIZE your information as training data to update its algorithms.
    - Fin.AI will NOT UTILIZE your information as training data to update its algorithms.

----Next page----
<u>Same demographic questions</u>

Study 6B

Thank you for your participation!

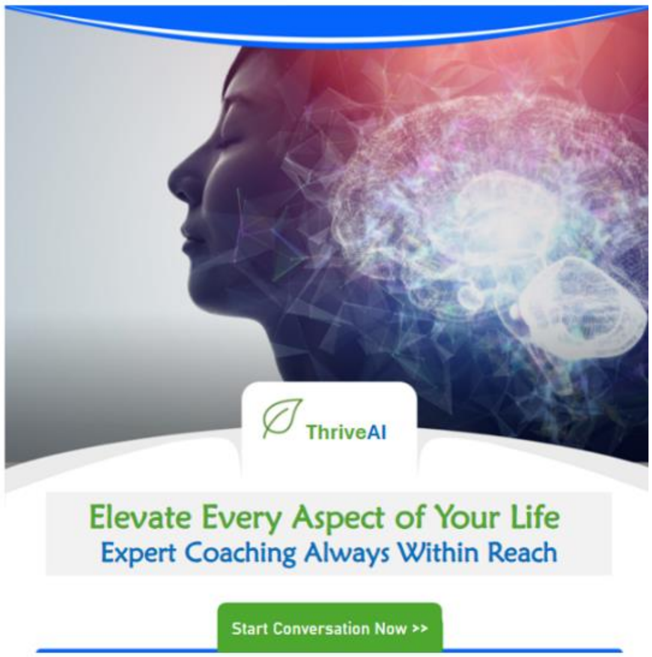
We are a team of market researchers working in collaboration with a group of app developers who are creating an AI-based life coaching service called ThriveAI.
ThriveAI is designed to support users to achieve their desired goals in all areas of their lives ranging from their career to their personal relationships. ThriveAI gives you personalized support and guidance for your goals through interactive conversations with you.

----Next page----

We are currently pilot testing ThriveAI with a small group of users before launching the application. Our goal is to gain insights into our potential user base. Please read the advertisement and service description provided on the following page.

----Next page----

[Control]



🌈 **Looking for Encouraging Support and Empowerment?** 🌈

🌟 **Meet ThriveAI!** 🌟

💬 **Interactive Conversations** — Personalized chats to get to know about you.

📚 **Tailored Responses** — Get the support and guidance you need to thrive in life.

📈 **Proven Success** — Benefit from what we've LEARNED from thousands of personal experiences.

🧠 **Completed Learning** — We do **NOT use your information** to **UPDATE** our knowledge base. Your information will **NOT be utilized** as **TRAINING DATA** for our learning process!

[Learning]

🌈 **Looking for Encouraging Support and Empowerment?** 🌈

🌟 **Meet ThriveAI!** 🌟

💬 ****Interactive Conversations**** — Personalized chats to get to know about you.

📚 ****Tailored Responses**** — Get the support and guidance you need to thrive in life.

📈 ****Proven Success**** — Benefit from what we've LEARNED from thousands of personal experiences.

🧠 ****Continuous Learning**** — We **use your information** to **UPDATE** our knowledge base. Your information will **be utilized** as **TRAINING DATA** for our learning process!

----Next page----
ThriveAI needs to know about you and your current situation in order to provide you with customized guidance. If you are interested in trying ThriveAI, please allow us to know about you by answering the question below.
** Please provide as much detail as you could when responding to the question. Your responses will be passed to the system for processing.**

- What areas (e.g., career, relationships, health, or personal growth) are going well, and which ones do you believe need improvement? What challenges do you anticipate on your journey toward achieving your goals? To tailor our approach to your success, we'd also love to know more about you—how would you describe yourself—personality, work style, or the way you typically handle setbacks or challenges?

----Next page----
Please answer this question based on the app advertisement you read earlier:
- Which of the following statements is correct?
    - ThriveAI will UTILIZE your information as training data to update its algorithm.
    - ThriveAI will NOT UTILIZE your information as training data to update its algorithm.

----Next page----
<u>*Same demographic questions*</u>