The Value of Man in AI + Man: Field Evidence from Small Business Lending*

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Abstract

We investigate the value of human loan officers in an AI + Man loan decision model, where loan officers decide on loan application outcomes based on recommendations from an AI model. Using proprietary loan-level data from a FinTech company that provides loans to small businesses, we find that the incremental contribution of loan officers to loan profits beyond AI recommendations increases with the soft information used in loan decisions and decreases with agency issues and cognitive constraints faced by loan officers. Further analyses indicate that using both the quantity and quality of approved loans to evaluate loan officers' performance enhances the value of using soft information, mitigates the adverse impact of agency issues, but exacerbates the adverse impact of cognitive constraints in loan decisions. Our results contribute to the literature on AI by documenting the conditions under which humans can create or destroy value in an AI + Man decision model.

Key words: artificial intelligence (AI); lending; soft information; agency issues; FinTech

JEL codes: G2, G21, G32, O33

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1 Introduction

In this paper, we examine the role played by human loan officers in an "AI + Man" decision model for small business lending, using the proprietary data from a FinTech company. The company uses an artificial intelligence (AI) model to process all loan applications, and loan officers then make final loan approval decisions based on the recommendations from the AI model. The deviation of the final decisions from AI's recommendations captures the value contributed by loan officers. Our aim is to understand the conditions under which loan officers can provide incremental value over recommendations from an AI decision model.

The motivation for the research question is three-fold. First, recent advancements in AI and machine learning have led to substantial investments by both corporations and governments (Agrawal, Gans, and Goldfarb 2019; Babina et al. 2024). For example, Gartner predicts that investments in AI will reach $1.5 trillion in 2025.[1] Many organizations have incorporated AI-driven decision processes and, in many cases, have replaced human decision-making with automated systems (e.g., Acemoglu et al. 2022). These developments raise an important question regarding the continued relevance and value of human judgment in environments increasingly mediated by AI: How can humans contribute in a meaningful way when working with sophisticated AI tools? Examining the value of humans in AI-supported decisions is thus a timely and economically significant topic.

Second, the existing literature compares the performance between fully automated decision systems and hybrid systems that combine algorithmic predictions with human judgment (e.g., Kleinberg et al. 2018; Cao et al. 2024). While such comparisons are informative, it is important to identify the conditions under which human intervention

[1] See details at https://www.gartner.com/en/newsroom/press-releases/2025-09-17-gartner-says-worldwide-ai-spending-will-total-1-point-5-trillion-in-2025.

improves upon or detracts from AI-generated recommendations. This question is particularly timely because more companies are providing AI assistance to workers. For example, a McKinsey report finds that that more than 76% of corporate executives expect workers to use AI tools for more than 30% of their daily tasks in the next five years.[2] Prior research provides suggestive evidence that human expertise remains valuable when information is noisy, when contextual interpretation is required, or when decisions involve soft information that is difficult to codify (e.g., Brynjolfsson, Mitchell, and Rock 2018; Cao et al. 2024; Jansen et al. 2025). A systematic examination of the conditions under which human discretion contributes positively can improve the design of AI–human collaboration frameworks, with implications for both organization structure and reskilling of workforce.

Third, the rapid expansion of FinTech platforms and the adoption of algorithmic credit scoring have transformed traditional lending practices (Fuster et al. 2019; Sutherland 2020; Gopal and Schnabl 2022). For example, Fuster et al. (2019) compare the performance of FinTech mortgage lenders and traditional ones and find that FinTech lenders process mortgage applications faster without sacrificing risk control. Yet many financial institutions continue to rely on loan officers, particularly when assessing borrowers for whom soft information is important (Stein 2002). Whether and when human judgment provides incremental value over AI in credit allocation is a critical question for banks seeking to balance efficiency and risk control. Understanding the role of humans in an AI-assisted lending model can inform FinTech companies and banks in staffing strategies and risk management in an era of accelerating technological integration (Kleinberg et al. 2018; McKinsey Analytics 2025).

To investigate the value of humans in an AI + Man decision model, we exploit the

[2] See details at https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/superagency-in-the-workplace-empowering-people-to-unlock-ais-full-potential-at-work#/.

proprietary data from a FinTech company in China (referred to as the focal company). The company provides loans to small business owners. Starting from the second half of 2023, the company shifts from an AI only decision model to an AI + Man hybrid decision model. Under this hybrid model, the company's proprietary AI model collects and analyzes extensive information about the borrowers. The AI model then provides recommendations on whether to approve the loan application, loan amount, interest rate, and term.[3] Based on AI recommendations, a short interview with the borrower and the front-end customer officer who solicits loan applications, loan officers make final decisions on whether to approve the loan, and if so, loan amount, interest rate, and term.

Using the loans approved in 2024 by the focal company, we calculate the profit based on loan officers' decisions and the profit based on AI recommendations. The difference between the two (the profit based on loan officers' decisions minus the profit based on AI recommendations, scaled by the amount dispensed to the borrowers), referred to as the deviation in profit, captures the value contributed by human loan officers in an AI + Man hybrid decision model.

We start by investigating whether on average human loan officers contribute value beyond AI recommendations. We find that the mean deviation in profit is negative (about -0.5%) and the median is close to zero (0.02%). In 52% of the cases, human loan officers contribute positively. In addition, the variation of deviation in profit is large, with an interquartile range of over 6%. The deviation in profit is primarily driven by the deviation in loan amount and to a lesser extent by the deviation in interest rate, deviation in term, and whether loan officers approve loans denied by AI. The statistics suggest that it is important to understand the *conditions* under which loan officers contribute positively or negatively.

[3] The AI model provides recommendations on loan amount, interest rate, and term even when it recommends denial of loan applications.

Based on prior research on the benefits and costs of using AI in the lending setting, we focus on three broad areas where loan officers' contributions might vary.

First, we focus on the soft information used by loan officers. Prior literature highlights the importance of soft information in lending decisions (e.g., Campbell, Loumioti, and Whittenberg-Moerman 2019). Taking advantage of the comments made by loan officers when making decisions, we code the length of the comments and collect the comments regarding borrowers' supply chain, whether borrowers will receive support from their family members, the explanations for previous or current lawsuits faced by borrowers, and whether borrowers are recommended by existing clients or acquaintances. Based on these proxies, we find that the use of soft information is positively correlated with the value contributed by loan officers. The effect ranges from 3.2% to 12.7% of the standard deviation of the deviation in profit.

Second, we turn to agency issues faced by loan officers. Unlike the AI system, loan officers are subject to agency issues, which might arise from personal connections or incentives to meet key performance indicators (KPIs). With respect to personal connections, we construct two proxies capturing personal connections between loan officers and borrowers and between loan officers and front-end customer officers. Personal connections might induce loan officers to be more lenient in loan decisions. We construct two variables based on incentives to meet KPI targets: (1) peer pressure when the loan officer is lagging behind colleagues' performance in the number of approved loans, and (2) the end of day on Fridays when the loan officer might want to meet weekly KPI targets. Based on these proxies, we find that the existence of agency issues is negatively correlated with the profit contributed by loan officers. The effect ranges from 9.3% to 15.5% of the standard deviation of the deviation in profit.

Lastly, we consider cognitive constraints of loan officers. Psychology theory suggests that humans become less effective in decision making when subject to cognitive constraints. We consider two dimensions of cognitive constraints: (1) complexity of loan applications and (2) mental fatigue. Using borrowers obtaining loans from other financial institutions and loan officers' lack of experience with borrowers' industry as proxies for complexity, we find that loan application complexity is negatively associated with the value created by loan officers. The effect ranges from 10.0% to 20.5% of the standard deviation of the deviation in profit. Using the peak hours of processing loan applications and the half an hour before dinner time to proxy for mental fatigue, we find that loan officers' contribution to profit is lower when experiencing fatigue. The effect is relatively small, ranging from 3.6% to 5.5% of the standard deviation of the deviation in profit.

To investigate whether the results are robust and to enrich the inferences, we conduct a few additional tests. First, on July 1, 2024, the focal company implemented a new performance evaluation policy for loan officers by explicitly recognizing the quality of approved loans, i.e., the default rate of loans approved in the previous 12 months, during evaluations. Up to this point, the inclusion of loan quality in loan officers' evaluations is less explicit. We find that after the implementation of the new policy, the use of soft information better enhances the value created by loan officers and agency issues (except peer pressure) reduce the value created by loan officers to a less extent. In contrast, after the implementation of the new policy, cognitive constraints have a more negative effect on the value created by loan officers, consistent with a greater cognitive demand for the loan officers after the new policy.

Second, for 61% of the loans approved by loan officers, AI's recommendation is to deny the applications. We refer to this group of loans as the override sample. We separately analyze the override sample and the non-override sample to investigate whether the results differ between these two subsamples. We find that the use of soft information enables loan officers to create more value in the override sample. The use of soft information is less critical when loan officers agree with AI's recommendations of loan approval. We also find that cognitive constraints of loan officers have a more negative effect on their contributions when they override AI's recommendations, which likely takes more effort than agreeing with AI's recommendations.

Third, we use Shapley values to evaluate the relative importance of the three groups of proxies. When including all the proxies in the regression at the same time, we find that soft information proxies contribute 10.36% of the explanatory power, agency issue proxies contribute 14.16%, and proxies for cognitive constraints contribute 38.16%. That is, the important factors affecting humans' value are cognitive constraints, followed by agency issues and soft information. These results imply that Fintech companies should pay close attention to cognitive constraints and agency issues faced by humans in an AI + Man decision model.

Lastly, when calculating the hypothetical profit based on AI's recommendations, instead of using the interest rate recommended by the AI model, we use the average interest rate charged by loan officers in the last month as the alternative interest rate for loans denied by the AI model. The idea is that had the company denied these loan applications, the fund would have been used for other loans, earning the average interest rate. Using this assumption to recalculate the deviation in profit, we obtain the same inferences.

Our paper contributes to the literature in two ways. First, it contributes to the literature on AI by examining the value of humans in an AI + Man decision model. Given that more and more companies are investing in AI to provide robot assistance to their employees, it is important to understand the value created by humans in an AI-assisted decision-making process. Conceptually, AI is a prediction technology, and humans can contribute by making judgements based on inputs that cannot be easily quantified or codified (Agrawal et al. 2019).

Empirically, our results suggest that humans can contribute by utilizing soft information. At the same time, agency issues and cognitive constraints can reduce humans' contribution. Our results can thus inform corporations in better designing the interactions between AI and workers to leverage both humans' and AI's advantage.

Second, our paper contributes to the literature on FinTech and banks. Loan decision is fundamentally a prediction problem, and AI and machine learning are prediction technologies. Whether to use AI to replace human loan officers and how to design a hybrid model by combining both the recommendations from AI and the inputs from human loan officers are increasingly important questions. Our results can inform FinTech companies and banks about staffing strategies and risk management in an era of accelerating technological integration.

Our paper is closely related to three papers: Liu (2022), Jansen, Nguyen, and Shams (2025), and Costello, Down, and Mehta (2020). Liu (2022) and Jansen et al. (2025) compare the performance of AI and human (i.e., AI vs. man) and find that AI outperforms man. Utilizing data from a small business lender, Liu (2022) shows that a machine learning model outperforms loan officers and that humans' underperformance arises partially from their constraints in processing hard information. He finds that humans use fewer pieces of hard information, tend to use linear functions, and tend to put a greater emphasis on salient signals. Jansen et al. (2025) use a car loan setting and find that machine underwriters outperform human underwriters. They find that human's underperformance is related to agency conflicts faced by human underwriters—their incentives to underprice loans to win the bid in auto loan applications—and human underwriters' poorer ability to process hard information in complex cases. Different from Liu (2022) and Jansen et al. (2025), our paper examines the value of humans on top of AI recommendations in an AI + Man setting. We find that human's ability to collect and process soft information enhances their contribution and agency issues reduce their contribution. In addition, human's cognitive constraints still matter even with the assistance of AI. Our analyses directly speak to human's decision efficiency in an AI-assisted mode.

Like our paper, Costello et al. (2020) examine an AI + Man setting. They conduct a field experiment in the setting of trade credit extension. While all lenders make decisions based on the recommendations of an automated system provided by a third-party platform, Costello et al. allow half of the trade credit lenders additional discretion in deviating from the machine's recommendations. They find that on average, allowing humans more discretion is associated with a greater reduction in credit risk, especially for private clients without social media accounts. Our paper extends Costello et al. (2020) in several ways. First, we examine whether human intervention in an AI + Man setting adds value in loan decisions. Costello et al. focus on trade credit extension. Unlike loans, trade credit extension is tied to the exchange of underlying goods or services. In addition, trade credit has a short duration and does not carry an explicit interest rate. Thus, the results based on the trade credit setting might not be generalizable to loans. Second and more importantly, while Costello et al. primarily focus on whether allowing human users a larger discretion from machine-based recommendations affects lending outcomes, we focus on how, or the conditions under which, human loan officers add or destroy value. We are able to observe the soft information used by, agency issues faced by, and cognitive constraints experienced by loan officers. Thus, our study sheds light on the conditions under which loan officers add or destroy value, i.e., how humans leverage their advantages in AI-aided systems.

2 Institutional background, related literature, and hypothesis development

2.1 Institutional background

The focal company of this study is a licensed lending company headquartered in Zhejiang Province, China. Established in December 2015, it is one of the first small business lending companies approved in the province. Since its inception, the company has positioned itself at the forefront of China's rapidly evolving small business lending sector. Its main clients are small business owners who require several hundred thousand RMB per loan application.

The company's loan approval process has evolved through three distinct stages. In the Expert Decision Phase (2016–2020), credit assessments were carried out by loan officers, who evaluated borrowers based on hard financial data and soft information, such as business reputation and relationship-based insights, which is difficult to quantify but essential for assessing borrowers' creditworthiness in opaque markets.

In the AI Decision Phase (2021–mid 2023), the company transitioned to a fully automated lending model. By leveraging big data and machine learning techniques, it established a risk control system that integrated data on clients' borrowing histories, income patterns, and consumption behaviors. An AI system evaluated all loan applications without human intervention, aligning with the broad FinTech trend toward algorithmic credit scoring and automated decision-making.

Since mid-2023, the company entered the AI + Man Decision Phase, prompted by regulatory and operational considerations. The cap on interest rates imposed by Chinese regulators has reduced the AI model's ability to offset high risks with interest rate adjustments. As a result, the company experienced an excessive rejection rate for loan applications, constraining its business growth. To address this issue, the company reintroduced expert judgment alongside algorithmic evaluation. Under this hybrid model, loan officers make the final loan approval decisions based on the recommendations of the AI system.[4] The underlying infrastructure of the AI system is built on state-of-the-art machine-learning methods, including gradient boosting algorithms such as XGBoost. The AI system

[4] The loan officers are newly hired and are not the same as those employed under the Expert Decision phase.

also includes modules for fraud detection and information verification. The company's proprietary modeling technology has been granted multiple patents in China.

The workflow under the current model is as follows. An applicant initiates a loan application through the company's mobile app, official website, or by visiting an offline branch. One of the company's front-end customer officers will assist the applicant in completing the application and collect relevant information, including demographic characteristics, socioeconomic attributes, and financial statements of the applicant's business. These inputs are then standardized and submitted to the AI system. The AI model assesses the credit risk using large-scale algorithms that analyze the submitted information as well as over 20,000 variables it collects, integrating large language models and image-recognition techniques in the analysis when applicable.[5] The AI model will generate a due-diligence report, which contains a recommendation (approval or denial) and the recommended loan amount, interest rate, and term. After receiving the AI report, one of the loan officers conducts an online meeting with both the applicant and the customer officer who handles the application. The meeting typically lasts about 30 minutes, during which the loan officer gathers additional information about the applicant and seeks clarifications on some issues when necessary. The loan officer then makes the final decision and files the decision report in the system.

Note that loan officers approve a line of credit (loan amount) to the clients. The client then decides how much to draw on the line of credit when needed. The company refers to each drawing as an invoice. On average, clients draw on the credit four times during the approved loan term. We refer to the line of credit as loan for brevity throughout the paper.

This AI + Man decision model provides an ideal setting to investigate the

[5] The AI model draws upon an extensive range of data sources, including the People's Bank of China credit registry, data purchased from third-party vendors, and records of individual consumption. It also uses clients' prior borrowing and payment information within the company. In total, the AI model uses over 20,000 variables.

complementary role of human expertise in lending decisions, in contexts where informational, agency, and behavioral frictions shape the value of human intervention.

2.2 Literature review

A growing literature examines the economic consequences of AI in financial decision-making, paying particular attention to how AI complements or substitutes for human judgment. Grennan and Michaely (2021) find that AI analysis adopted by FinTech firms can improve price informativeness and can potentially substitute for traditional sell-side research. Coleman, Merkley, and Pacelli (2022) document that the recommendations of Robo-Analysts—human analyst-assisted computer programs—contain positive long-term investment value and are less biased and more frequently updated than human analysts' recommendations. van Binsbergen et al. (2023) use their AI models to detect biases in human analysts' forecasts. Exploiting the one-month ban on ChatGPT in Italy, Bertomeu et al. (2025) find that analysts integrate large language models (LLMs) into their workflow, which influences forecasting behavior and outcomes. This line of research thus supports the notion that AI is useful for security analyses. Extending to firm decision setting, prior research documents productivity gains from AI adoption (e.g., Fedyk et al. 2022; Jansen et al. 2025). For example, Babina et al. (2024) find that firms' investments in AI can lead to growth in sales and market valuation, which is partially driven by the effect of AI investments on product innovation.

Another line of literature investigates how AI shapes the labor market. For example, Abis and Veldkamp (2024) find that new data and AI technologies shift labor shares within financial firms and that these firms rely less on labor in their production function. Using establishment-level data, Acemoglu et al. (2022) document that as establishments increase investments in AI, the hiring of non-AI positions decreases.

Particularly relevant to our study, Cao et al. (2024) compare the performance of human analysts with an AI analyst built by the authors (i.e., AI vs. man). They further compare the performance of the AI analyst with that of a "Man + AI" analyst, which uses human analysts' forecasts as an additional input to the AI analyst. They find that human inputs are more valuable when covering firms that are more illiquid, have more intangible assets, and have higher earnings volatility and distress risk. Complementing Cao et al., we focus on the value of human intervention in an AI + Man setting, where human loan officers make the final loan decision based on the recommendations of an AI system. That is, unlike the setting in Cao et al., humans make the final decisions in our setting, which is close to companies providing AI assistance (i.e., "robot assistants") to their employees in practice as the focal company does. Our setting allows us to examine the value of humans over an AI-based decision model and how the value of humans varies with the soft information used by, agency costs faced by, and cognitive constraints experienced by human loan officers. In addition, our evidence speaks to the synergies of man and machine in the loan decision setting.

2.3 Hypothesis development

2.3.1 Main hypothesis

A central question in the adoption of an AI + Man decision model is whether human intervention improves or impairs credit decision quality. Theoretical and empirical research provides reasons for both positive and negative effects, leading to a prediction of an ambiguous net effect.

The potential benefits of human intervention. A key argument in favor of human intervention centers on the informational limitations of AI systems (Agrawal et al. 2019). While modern machine-learning algorithms excel at processing hard information—verifiable, structured data such as income, education, and spending patterns, they currently have limited capabilities to acquire and interpret soft information, which often requires personal interactions, contextual judgment, and tacit knowledge. In the lending setting, soft information can include impressions of borrowers' integrity, the credibility of their narratives, and nuanced aspects of business conditions, all of which are difficult to codify or quantify algorithmically at the current stage. For example, in our setting, loan officers briefly meet with loan applicants and customer officers and loan decisions are influenced by loan officers' perceptions of applicants and additional information acquired during the meeting, such as family support and contextual business information.

The value of soft information is well documented in the literature (e.g., Campbell et al. 2019). Liberti and Petersen (2019) highlight that soft information plays a critical role when borrower quality cannot be fully inferred from historical or quantitative indicators, especially for small-business and relationship lending. Gerken and Painter (2023) show that local or contextual knowledge can improve financial decision-making by enriching the information set beyond what standardized analytical tools capture. These findings suggest that human loan officers can contribute complementary insights over AI systems.

In addition, while AI models are increasingly sophisticated, they remain imperfect predictors. Agrawal et al. (2019) argue that the value of human judgment resides in how predictions are interpreted and acted upon. In the setting of lending decisions, this implies that human loan officers can improve on AI recommendations, particularly in borderline cases or when borrowers exhibit atypical characteristics.

Taken together, prior research suggests that human intervention can enhance lending decisions by providing soft information, contextual reasoning, and judgmental oversight that complement AI-driven lending models.

The potential costs of human intervention. Despite the potential benefits, theoretical and empirical studies caution that human intervention can also reduce lending decision quality. First, loan officers may face misaligned incentives that distort assessments. For example, loan officers might be subject to KPI targets related to loan amounts and approve poor quality loans to meet the KPI targets and to increase their compensation. In such cases, human intervention can reduce lending decision quality relative to AI recommendations.

Second, behavioral frictions related to algorithm aversion, which refers to the phenomenon that workers avoid or reduce the reliance on AI assistance even when doing so reduces task performance, can decrease decision quality (e.g., Bockstedt and Buckman 2025). Jussupow, Benbasat, and Heinzl (2024) show that individuals frequently underweight or reject algorithmic inputs—even when the algorithm is demonstrated to be more accurate. It is also possible that human decision-makers override algorithmic recommendations to demonstrate their value and to keep their jobs. In the lending context, algorithm aversion may lead loan officers to revise AI recommendations excessively, thereby reducing the potential gains from algorithmic decisions.

Lastly, cognitive constraints of human decision-makers or mental fatigue can reduce the value of human intervention (e.g., Baumeister et al. 1998). For example, Hirshleifer et al. (2019) document that financial analysts become less accurate in their earnings forecasts when their workload accumulates through the day, suggesting that human judgment worsens under cognitive overload. If loan officers become overly fatigued or inattentive due to factors such as workload and upcoming holidays, their intervention may introduce noise rather than value.

Overall, agency problems, behavioral frictions, and cognitive constraints can cause human intervention to either add no value or introduce additional errors relative to AI-driven decisions.

An ambiguous net effect. Loan officers may complement AI by supplying soft information and contextual insights, yet they may also hinder performance because of misaligned incentives, ineffective use of algorithmic recommendations, and/or cognitive constraints. Accordingly, the net effect of incorporating human judgment into AI-assisted lending decisions is ambiguous. Thus, our first hypothesis (in the null form) is stated as follows:

> *H1: Ceteris paribus, the net effect of human intervention on the quality of AI-assisted lending decisions is unclear.*

2.3.2 Cross-sectional variation

In this section, we discuss the conditions under which human intervention is more or less likely to improve on AI's lending decisions. These conditions reflect the variation in (1) the use of soft information, (2) the severity of agency conflicts faced by loan officers, and (3) cognitive constraints of loan officers.

The use of soft information. Prior research emphasizes that human judgment is particularly valuable when soft information—qualitative, non-standardized, or relationship-based information—is critical for assessing borrower risk (Liberti and Petersen 2019). In settings where borrowers lack sufficient credit histories or where business risk is difficult to evaluate based on hard information, loan officers may provide incremental value by collecting, interpreting, and incorporating soft information that AI systems do not have access to or cannot process effectively. For example, new borrowers may have insufficient digital footprints or verifiable records, leading to greater value for in-person assessments, interviews, and contextual judgment. In such cases, the marginal value of human intervention is likely to be higher. Our second hypothesis is thus stated as follows:

> *H2: Ceteris paribus, human intervention is more likely to improve the quality of loan decisions when soft information is used.*

Agency problems faced by loan officers. Although human input can add value, loan officers may be subject to agency issues that distort their decisions. These frictions reduce the quality of human adjustments to AI-generated recommendations, leading to poorer loan decisions. For example, personal connections between loan officers and borrowers, such as shared community ties, may create favoritism, reducing the value of human intervention. In addition, loan officers usually have loan approval targets, creating incentives to approve marginal borrowers to meet targets. Accordingly, when agency problems faced by loan officers are more severe, human adjustments to AI recommendations are less likely to add value. Our third hypothesis is stated as follows:

> *H3: Ceteris paribus, human intervention is less likely to improve the quality of loan decisions when loan officers face more severe agency problems.*

Cognitive constraints and fatigue. Another source of cross-sectional variation arises from cognitive constraints and fatigue. Research in behavioral economics and accounting demonstrates that decision fatigue can reduce the quality of professional judgment, particularly under time pressure or with high workloads (Hirshleifer et al. 2019). In the lending context, loan officers who have peak-period workloads may experience fatigue that reduce their ability to effectively evaluate borrowers' information or critically assess AI's recommendations. Under fatigue, loan officers may rely on heuristics, become less attentive to risk indicators, default to AI recommendations without appropriate scrutiny. Our last hypothesis is thus stated as follows:

> *H4: Ceteris paribus, human intervention is less likely to improve the quality of loan decisions when loan officers are subject to more cognitive constraints.*

3 Sample and research design

3.1 Sample

We start with the population of 28,137 loans approved by the focal company in 2024. We do not consider loans approved in the second half of 2023 because loan officers likely need time to learn how to work with AI recommendations. We do not consider loans approved in 2025 either because we need time to evaluate the outcomes of the approved loans. We drop 6,730 loans that have not matured at the time of data collection. We further drop 2,706 loans with missing variables, 52 loans approved by inexperienced loan officers, i.e., those who approved fewer than 100 loans in 2024,[6] and 159 singletons due to the inclusion of fixed effects. Table 1 provides the summary of sample selection.

Panel A of Table 2 provides descriptive statistics on loan outcomes based on AI recommendations and loan officers' decisions. The average loan amount is CNY126,947 under AI recommendations, lower than the average of CNY161,846 based on loan officers' decisions. The average interest rate recommended by AI is 18.15%, higher than what's decided by loan officers (14.51%). The average term of the line of credit recommended by AI is 16.58 months, shorter than what's approved by loan officers (24.62 months). All the differences are significant at the 1% level. These statistics indicate that on average, loan officers approve a larger amount of loans with a lower interest rate and a longer term than AI recommendations.

3.2 Loan profit calculation

Following Jansen et al. (2025), we calculate the profit of each invoice of the loan using realized or expected cash flows as follows:

$$Profit = \sum_m [PV(Payment_m) + PV(Recovery|Default)] - Initial\ Investment, \quad (1)$$

where *Profit* is the profit of the invoice for the company, m denotes month m, PV is the present value calculated using the corresponding Shanghai Interbank Offered Rate (Shibor), $Payment_m$ is the payment made by the borrower in month m, which includes both the interest payment and the repaid principal of the loan, *Recovery|Default* is the recovered principal and accrued interest upon default, and *Initial Investment* is the dispensed loan amount.

To evaluate the deviation of loan officers' decisions from AI's recommendations, we calculate *Profit* based on loan officers' decisions and based on AI's recommendations. We calculate *Profit* based on loan officers' decision using the dispensed loan amount and realized

[6] The average (median) number of approved loans across loan officers in 2024 is 792 (720).

cash flows and denote it as *Profit-$_{Man}$*. Appendix A provides an example of the calculation.

The calculation of loan profit based on AI's recommendations requires additional assumptions. First, we assume that the hypothetical dispensed amount under AI's recommendations is in proportion to the actual dispensed amount, with the proportion calculated as AI's recommended credit amount over the credit amount approved by the loan officer. The repaid principal under AI's recommendation is similarly calculated in proportion to the actual repaid principal. Second, we use AI's recommended interest rate and the hypothetical dispensed amount under AI's recommendations to calculate interest payment. Because borrowers typically receive interest rate discount, we assume that the same interest rate discount applies to interest payment under AI's recommendation as well. Based on these assumptions, we derive the hypothetical dispensed amount, repaid principal, paid interest, and calculate *Profit* accordingly, denoted as *Profit-$_{AI}$*. Please refer to Appendix A for an example of the calculation of *Profit-$_{AI}$*.

Because we do not observe the loan outcome under AI's recommendations, the estimation of *Profit-$_{AI}$* contains measurement errors. However, the errors are unlikely to bias the results for H2-H4 because they are unlikely to be correlated with the proxies for soft information, agency issues, or cognitive constraints. In addition, we conduct sensitivity tests by using alternative measurements and obtain the same inferences, as discussed in Section 5.

We calculate the deviation in profit of loan officers' decisions from AI's recommendations as follows:

$$Deviation\_Profit = 100 \times \frac{Profit_{-Man} - Profit_{-AI}}{Invoice\ Amount_{-Man}}, \tag{2}$$

where *Invoice Amount$_{_Man}$* is the total dispensed loan amount to the borrower. For loans with multiple invoices (i.e., multiple drawings by borrowers), we aggregate the profit at the invoice level to obtain the loan-level profit. *Deviation_Profit* reflects the quality of loan decisions and captures the value created by human loan officers in the AI-assisted lending decisions.

3.3 *Research design*

To test hypotheses H2-H4, we estimate the following regression:

$$\begin{aligned} Deviation\_Profit_l &\\ = \alpha + \beta_1 Soft\_Information_l + \beta_2 Agency\_Issue_l &\\ + \beta_3 Cognitive\_Constraint_l + \varepsilon_l\,, & \end{aligned} \tag{3}$$

where subscript *l* represents loan *l*. *Soft_Information* is the proxy for soft information used by loan officers in the approval process. *Agency_Issue* is the proxy for agency issues faced by local officers. *Cognitive_Constraint* is the proxy for cognitive constraints loan officers are subject to. We describe these proxies in the next section when we report the analyses. A positive coefficient on these variables indicates that these variables enhance the value contribution of human loan officers, while a negative coefficient indicates that they reduce the value contributed by human loan officers.

Because *Deviation_Profit* is calculated based on the difference between loan officer's decision and AI recommendation for the same loan, loan characteristics and borrower characteristics are held constant. We include month, borrowers' industry, and loan officer fixed effects to control for time trend, time-invariant industry characteristics, and inherent attributes of loan officers. The *t*-statistics are calculated using standard errors clustered at the loan officer level.

4 Main tests

4.1 *Value of Man in AI + Man: Test of H1*

To test H1, we compare the profit of loans based on AI recommendations and loan officers' decisions. Panel A of Table 3 reports the results. We find that the average profit based on AI recommendations is CNY 13,376.67, and the average profit based on loan officers' decisions is CNY 13,153.45. The difference is significant at the 1% level.

To formally test H1, we calculate the deviation in profit of loan officers' decisions from AI recommendations, *Deviation_Profit,* for each loan. As reported in Panel B of Table 3, the mean of *Deviation_Profit* is -0.495%. A closer look at the distribution indicates that this is driven by the long tail on the left. As shown in Figure 1, the distribution of *Deviation_Profit* centers around zero, with a median of 0.020%. An untabulated test indicates that *Deviation_Profit* is positive for 52.11% of the loans. However, there is a long tail on the left with extreme negative values. After winsorizing the variable at 1st and 99th percentiles, the minimum is -27.36%, while the maximum is 11.24% (untabulated). *Deviation_Profit* has a large variation – the standard deviation is 6.776%.

To understand what drives the difference in profit, we run a regression of *Deviation_Profit* on the difference in loan parameters between loan officers and AI —amount (*Deviation_Amount*), interest rate (*Deviation_Rate*), term (*Deviation_Term*)—and the likelihood of loan officers overriding AI's recommendations of loan denial (*Override*). Panel B of Table 3 reports the descriptive statistics on these variables. The mean of *Deviation_Amount* is 2.134 times AI's recommended loan amount, the mean of *Deviation_Rate* is -3.64%, and the mean of *Deviation_Term* is 8.04 months. The mean of *Override* is 0.609, suggesting that for 60.9% of the loans approved by loan officers, AI's recommendation is denial.[7]

Table 4 reports the regression results. We control for month, industry, and loan officer fixed effects. When the four variables (*Deviation_Amount*, *Deviation_Rate*, *Deviation_Term*, and *Override*) are included individually in Columns (1)-(4), all of them are significantly positively correlated with *Deviation_Profit* (t = 65.56, 12.14, 6.23, and 4.70, respectively). These results suggest that when loan officers increase loan amount, interest rate, and term and

[7] An untabulated analysis indicates that loans denied by AI but approved by loan officers have a smaller amount, lower interest rate, longer term, and lower profit than those approved by both AI and loan officers.

override AI's denial decisions, their contribution to profit is higher. When we include all the four variables at the same time, as reported in Column (5), the inferences remain the same. In the last column of Table 4, we report the Shapley value of each variable.[8] We find that *Deviation_Amount* has the highest contribution to the explanatory power of the model (89.03%), followed by *Deviation_Rate* (5.58%). *Deviation_Term* and *Overide* contribute little to the explanatory power.

In sum, the evidence is inconclusive regarding H1. Human loan officers' value by deviating from AI recommendations is positive for more than half of the loans but has a negative mean due to some extreme negative values. Moreover, the deviation in profit has a large variation. Thus, it's important to understand the conditions when humans add or subtract value by deviating from AI's recommendation.

4.2 Soft information and the deviation in profit – Tests of H2

H2 states that the value of human loan officers in an AI + Man decision-making setting increases with the use of soft information by loan officers. While the concept is straightforward, the challenge in the literature has been how to capture soft information used by loan officers. We overcome this challenge by obtaining access to the comments made by loan officers when approving loans. Based on these comments, we construct five proxies for soft information: (1) the length of the comments made by loan officers (*Comment_Long*); (2) the discussion of supply chain status of borrowers' businesses (*Supply_Chain*); (3) the support for borrowers from family members (*Family_Support*); (4) the explanation for the past and current lawsuit faced by the borrowers (*Lawsuit_Explanation*); and (5) the referral from existing clients or loan officers' acquaintances (*Referral*). Appendix B provides detailed definitions of these variables.

[8] We evaluate the relative importance of the determinants based on Shapley values (Huettner and Sunder 2012), which utilize an iterative process to decompose R-squared into the portions attributable to each variable.

First, given that the comments are mainly about information not used by AI and primarily contain soft information, the longer the comments are, the more soft information loan officers use in their decisions. Second, some comments discuss the status of the borrowers' businesses in the supply chain or borrowers' relationship with their suppliers and customers. Such information can help loan officers to better evaluate borrowers' creditworthiness. For example, one loan officer notes that "The construction business has been running for two years, maintains stable relationships with its clients, and has collected receivables in a timely fashion." Another loan officer notes that "The client receives supply-chain credit from Shanghai XYZ Corp. to pay his suppliers on a loan basis, with annual transactions of around CNY 50 million. The credit is collateralized by receivables. Because there are no details on loan agreements and interest obligations, these details are not reflected in the online credit report." Third, the support from family members can increase borrowers' ability to pay interests and principal. The old Chinese saying that "Sons will pay the father's debt" highlights that the support from family members is a strong form of loan guarantee. For example, one loan officer notes that "The client operates a food processing business. … The client's son is willing to co-pay interests, indicating a strong intent to pay the loan." Another loan officer notes that "The client's two daughters have low debt and are willing to support the business." Fourth, while borrowers involved in lawsuits in general have higher risk, their ability to pay interest and debt depends on the actual situation. For example, one loan officer notes that "The client has a legal case pending, but he is the plaintiff." Another loan officer notes that "The client's business was previously involved in legal cases, but he has provided proof of settlement, and all cases are closed." Lastly, personal relation is well-regarded in China, and referring a friend to a business has the implicit "guarantee" of the person's integrity and creditworthiness.

Panel B of Table 2 reports descriptive statistics on these variables. About 26.9% of the loans have long comments from loan officers, 2.4% of the loans mention supply chain information in the comments, 7.7% of the loans indicate family support, 8.3% of the loans provide explanations for lawsuits, and 34.3% of the loans are referrals by existing clients or acquaintances. Appendix C reports the correlation between these variables. The correlation coefficients are generally small, indicating that they capture different dimensions of soft information used by loan officers.

We then use these five proxies to explain *Deviation_Profit* and report the regression results in Table 5. We find that the coefficients on all five proxies (*Comment_Long*, *Supply_Chain*, *Family_Support*, *Lawsuit_Explanation*, *Referral*) are significantly positive (t = 3.18, 1.97, 7.37, 2.67, and 2.48, respectively). Compared with other loans, loan officers' contribution in profit is higher by 7.6% (= 0.517/6.776) of the sample standard deviation of *Deviation_Profit* for loans with longer comments from loan officers, by 7.5% for loans with information on borrowers' supply chain status, by 12.7% for loans indicating support for borrowers from family members, by 8.8% for loans with explanations for lawsuits faced by borrowers, and 3.2% for loans referred by existing clients or acquaintances.

In sum, these results indicate that human loan officers can create value in an AI + Man decision mode through the use of soft information.

4.3 Agency issues and the deviation in profit – Tests of H3

H3 states that the value of human loan officers in an AI + Man setting decreases with agency issues faced by loan officers. We construct four proxies for agency issues faced by loan officers: (1) the hometown tie between loan officers and the borrowers (*Hometown_Tie*), (2) the potential connection between loan officers and front-end customer officers handling loan applications (*Lower_Rate*), (3) the peer pressure in achieving KPIs (*Peer_Pressure*), and (4) the end of day on Fridays (*FridayEOD*). Appendix B provides detailed definitions of these variables.

First, hometown tie—the loan officer and the borrower sharing the same place of origin—is one of the most widespread sources of networks in the Chinese society. Prior research finds that hometown ties affect a wide range of decisions, such as politicians' career progression (Fisman et al. 2020), quality of government monitoring (Chu et al. 2021), and audit quality (Deng, Zhang, and Liu 2023). We thus expect loan officers to be more lenient with borrowers from the same hometown (e.g., by charging a lower interest rate), reducing loan quality. Second, because we do not have personal information about the front-end customer officers who help borrowers with loan applications, we cannot directly observe the relationship between loan officers and customer officers. For 69% of the approved loans, customer officers provide a suggested interest rate, which is generally lower than that decided by loan officers, likely reflecting customer officers' incentives to use low interest rate to attract loan applications. In about 25.1% of the cases with recommended interest rates from customer officers, the interest rate decided by loan officers is lower than or equal to the rate recommended by customer officers. We argue that such cases likely reflect the personal connection between loan officers and customer officers, reducing the value of human intervention.[9] Third, the number of approved loans is a critical KPI for loan officers. The loan officers with a higher number of loan approvals are likely to be awarded a higher bonus. Thus, we expect the loan officers who are lagging in processing loan applications to be under pressure to increase the number of loans approvals at the expense of decision quality.[10] Lastly, in a similar vein, we expect loan officers to rush in processing loan applications at the end of Fridays in an attempt to meet weekly targets, either set by themselves or implicitly by the focal company.

[9] Such cases may also reflect the personal connections between loan officers and borrowers that are not captured by hometown ties.

[10] The focal company intentionally creates peer pressure among loan officers. It installed a large screen in the meeting room for loan officers to display real-time approval progress, allowing loan officers to observe their colleagues' workloads and progress in real time.

As reported in Panel B of Table 2, 5.0% of the loans are approved by loan officers with hometown ties with borrowers, 17.3% of the loans have a lower rate than or the same rate as recommended by customer officers,[11] 55.1% of the loans are approved under peer pressure, and 2.9% of the loans are approved in the last working hour on Fridays. As indicated in Appendix C, these variables are not highly correlated with each other, indicating that they capture different dimensions of agency issues faced by loan officers.

Table 6 reports the regression results. We find that the coefficients on *Hometown_Tie*, *Lower_Rate*, *Peer_Pressure*, and *Friday_EOD* are significantly negative (t = -4.10, -6.22. -5.23, and -2.24, respectively). Compared with other loans, loan officers' contribution to profit is lower by 15.5% (= -1.050/6.776) of the sample standard deviation for loans approved by loan officers who have hometown ties with borrowers, by 13.8% for loans with interest rates lower than or the same as what's recommended by customer officers, by 10.4% for loans approved by loan officers under peer pressure, and by 9.3% for loans approved in the last working hour on Fridays.

These results indicate that loan officers faced with agency issues, arising from personal connections with borrowers and customer officers or the pressure to achieve KPIs, create less value, or destroy value, by deviating from AI's recommendations.

4.4 Cognitive constraints and the deviation in profit – Tests of H4

H4 states that the value of human loan officers in an AI + Man decision setting decreases with cognitive constraints faced by loan officers. We consider two dimensions of cognitive constraints: (1) the complexity of loan applications, and (2) loan officers' mental fatigue.

With respect to the complexity of loan applications, we construct two proxies: (1) loans

[11] We set *Lower_Rate* as zero for loans without recommended interest rates from customer officers. Dropping these observations yields similar results for *Lower_Rate*.

applied by borrowers who have loans from other financial institutions (*Multi_Loan*), and (2) lack of industry experience of loan officers (*Ind_Experience_L*). First, when a borrower has loans from other financial institutions, the loan officer needs to consider the implications of a larger amount of funding for the borrower's business, the seniority of the loan from the focal company, and the implications of having other loans for the borrower's ability to pay interests and principal. Thus, loan officers' cognitive constraints likely lead to less value-adding decisions over AI's recommendations in such situations because AI has access to extensive information of borrowers and is adept at processing complicated cases (Liu 2022). Second, each individual loan officer is unlikely to be an expert to evaluate business conditions in all industries. If a loan officer is evaluating loan applications from an industry in which she does not have a lot of experience, her contribution is likely to be lower. As reported in Panel B of Table 2, 38.3% of the loans are applied by borrowers who have loans from other financial institutions, and 21.6% of the loans are approved by loan officers who are less experienced with loan applications from the borrowers' industry. As reported in Appendix C, the two variables are positively correlated with each other, but the correlation coefficient is very small (0.024).

Panel A of Table 7 presents the regression results. The coefficients on *Multi_Loan* and *Ind_Experience_L* are significantly negative (t = -9.37 and -4.94, respectively). Compared with other loans, loan officers' contribution to profit is lower by 20.5% (= -1.388/6.776) of the sample standard deviation for loans where the borrowers have obtained loans from other institutions and by 10.0% for loans approved by loan officers who have less experience in processing loan applications from the borrower's industry.

With respect to mental fatigue, we construct two proxies: (1) the hours in which loan officers approve the highest number of loans, i.e., 10-11am and 4-5pm (*Peak_Hour*), and (2) the half hour before dinner time, i.e., 4:30-5pm (*Before_Dinner*). Psychology theory suggests that mental fatigue occurs after a prolonged period of cognitive activities and can impair humans' cognitive ability and quality of decision-making (e.g., Shleifer et al. 2019). It thus follows that loan officers will be more likely to experience mental fatigue and make poor decisions when processing a large number of loan applications in a short period or after a long day's work. As reported in Panel B of Table 2, 25.6% of the loans are approved during peak hours,[12] and 8.0% of the loans are approved in the half hour before dinner time. Due to the overlap in the time period of the two proxies, they are positively correlated with each other, with a correlation coefficient of 0.503, as reported in Appendix C.

Panel B of Table 7 presents the regression results based on these two proxies. The coefficients on *Peak_Hour* and *Before_Dinner* are significantly negative (t = -2.46 and -2.03, respectively). Compared with other loans, loan officers' contribution to profit is lower by 3.6% (= -0.243/6.776) of the sample standard deviation for loans approved during peak hours and by 5.5% for loans approved right before dinner time.

Overall, these results suggest that loan officers' contribution over AI's recommendations is lower when approving complex loan applications and when experiencing mental fatigue.

5 Additional analyses

In this section, we report a few additional analyses and sensitivity tests to enrich the results and to ensure that the results are robust to alternative research design.

5.1 Separate analyses for loans approved in the first and second half of 2024

The focal company did not have a formal performance evaluation policy for loan officers when it first transitioned to the AI + Man decision model. Loan officers were compensated with a fixed salary negotiated with the company and a bonus. On July 1, 2024,

[12] In the focal company, loan officers start working at 8am. The official working hours end at 5pm. However, the company provide free dinner at 5pm. Many loan officers stay for dinner and work afterwards for a couple of hours. Thus, the number of working hours is longer than 8.

the focal company started to implement a new policy on the evaluation of loan officers. The evaluation considers both the number of loans approved and the default rate of loans approved in the previous 12 months, with both dimensions receiving equal weights. That is, the company explicitly considers both the quantity and quality of approved loans for the second half of 2024, while up until this point the consideration of loan quality is not explicit. This new policy encourages loan officers to pay closer attention to the quality of loan decisions. Increasing the number of approved loans at the expense of loan quality will directly reduce their performance and compensation in the future. We thus expect that loan officers are more conservative in approving loan applications in the second half of 2024. Thus, the impact of soft information, agency issues, and cognitive constraints might be different for the second half of 2024 compared with the first half. To test this, we replicate the main tests separately for loans approved in the first half of 2024 and in the second half of 2024.

Table 8 reports the regression results. Panel A focuses on soft information. We find that soft information proxies are significant in explaining *Deviation_Profit* for the loans approved in both periods. However, the tests of the difference in coefficients indicates that the use of soft information is significantly more positive in explaining *Deviation_Profit* in the second half than in the first half; the difference in coefficients on *Comment_Long*, *Family_Support*, and *Lawsuit_Explanation* are significantly different from zero at the 0.10 level or better. These results suggest that soft information plays a more important role in loan officers' decisions and contribution to profit when loan quality is more important to loan officers.

Panel B reports the regression results for agency issues. We find that all agency issue proxies are significantly negatively associated with *Deviation_Profit* for loans approved in the first half of 2024. However, only *Lower_Rate* and *Peer_Pressure* are significant in explaining *Deviation_Profit* for loans approved in the second half. The coefficients are more negative in the first half of 2024 than in the second half of 2024 for all proxies except *Peer_Pressure*. These results suggest that by emphasizing loan quality, the focal company is able to partially mitigate the agency issues faced by loan officers.

Lastly, Panel C reports the regression results for cognitive constraints. We find that while the two complexity proxies are important in explaining *Deviation_Profit* in both periods, the coefficients are significantly more negative for the second half of 2024 than for the first half. In addition, mental fatigue proxies are only significant for the second half of the year, suggesting that loan decisions take a greater toll on loan officers when loan quality is an important consideration.

Overall, these results indicate that a well-designed performance evaluation framework can shape loan officers' decisions. The emphasis on loan quality can induce loan officers to rely more on soft information, partially mitigate agency issues faced by loan officers, but exacerbate the negative impact of cognitive constraints.

5.2 Separate analyses for the override and non-override samples

As noted earlier, for 60.9% of the loans approved in 2024, AI's recommendation is to deny the loan applications (referred to as the override sample). It is likely that when loan officers decide against AI's recommendation of denial, they must have strong reasons to do so. It is also likely that loan officers' value is lower in cases where both AI and loan officers approve loan applications (referred to as the non-override sample). In this section, we investigate whether our results differ for these two subsamples of loans.

Table 9 reports the regression results. Panel A reports the results for soft information. We find that all soft information proxies except *Supply_Chain* are significantly positive in explaining *Deviation_Profit* in the override subsample. In contrast, for the non-override sample, only *Comment_Long* and *Family_Support* are significantly positive in explaining *Deviation_Profit*. The difference in the coefficients is significant for *Family Support* and

Lawsuit_Explanation. These results suggest that the use of soft information enables loan officers to create more value when overriding AI's recommendations of denial.

Panel B reports the regression results for agency issues. While the coefficients on all proxies are significantly negative in the override sample, only the coefficients on *Lower_Rate* and *Peer_Pressure* are significantly negative in the non-override sample. The difference in the coefficients is significant for *Hometown_Tie* and *Lower_Rate*, albeit with different signs.

Panel C reports the regression results for cognitive constraints. We find that all proxies except *Peak_Hour* are significantly negative in explaining *Deviation_Profit* in the override sample. In contrast, for the non-override sample, only *Multi_Loan* is significantly negative in explaining *Deviation_Profit*. The coefficients on *Multi_Loan* and *Ind_Experience_L* are significantly more negative for the override sample than for the non-override sample. These results suggest that cognitive constraints of loan officers have a more negative effect on their contributions when they override AI's recommendations of denial.

Overall, these results suggest that when loan officers override AI's recommendations, they more effectively use soft information. At the same time, their cognitive constraints have a more negative effect, likely due to a greater cognitive demand for such decisions.

5.3 The relative importance of soft information, agency issues, and cognitive constraints

To investigate whether results on individual variables examined above (Tables 5-7) hold when other variables are also included, we estimate a regression by including all proxies for soft information, agency issues, and cognitive constraints at the same time. Table 10 reports the regression results. The results continue to hold for all proxies except *Friday_EOD*, which is marginally significant (t = -1.62), and *Peak_Hour* and *Before_Dinner*, which are insignificant, likely due to the high correlation between the two. We also estimate the Shapley values for all variables to evaluate their relative importance in explaining *Deviation_Profit*. Collectively, the soft information proxies contribute 9.03% of the explanatory power, agency issue proxies contribute 18.27%, and proxies for cognitive constraints contribute 33.11%. In terms of individual proxies, the five most important ones are *Multi_Loan* (30.11%), *Lower_Rate* (8.37%), *Peer_Pressure* (5.82%), *Hometown_Tie* (3.65%), and *Comment_Long* (3.22%).

5.4 Alternative interest rate for loan applications denied by AI

In the main analysis, for the loan applications denied by AI but approved by loan officers, we calculate the hypothetical profit based on AI recommendations using the interest rate recommended by AI. The underlying assumption is that had AI recommended loan approval, that would be the interest rate charged on the borrower. However, we notice that the interest rate for many such loans is very high; AI charges sufficiently high interest rates to compensate for the credit risk for the risky borrowers. Whether such rates are practical, i.e., whether the borrowers are willing to borrow money with such a high interest rate, is unclear. In addition, had the company followed AI's recommendations, those loan applications would have been denied. The funds used for these loans would have been allocated for other investments, i.e., loans to other borrowers. We thus conduct a sensitivity test by using the average interest rate charged on all loans approved in the previous month as the alternative interest rate for the loans denied by AI. We calculate the hypothetical profit for each loan based on AI's recommended amount and the alternative interest rate and derive the difference in profit between loan officers' decisions and AI recommendations (*Deviation_Profit*) accordingly.

We replicate the tests of H2-H4 using this new measure. For brevity, Table 11 only reports the coefficients on the variables of interest. The inferences remain the same, except that the coefficient on *Supply_Chain* is marginally significant (t = 1.52).

5.5 Alternative research design

In an untabulated test, we use an alternative research design to test H2-H4. Instead of taking the difference between $Profit_{\_Man}$ and $Profit_{\_AI}$, we regress ln($Profit_{\_Man}$) on ln($Profit_{\_AI}$) and the proxies for soft information, agency issues, and cognitive constraints. That is, we do not force the coefficient on $Profit_{\_AI}$ to be one in explaining $Profit_{\_Man}$. Untabulated tests indicate that our inferences remain the same.

6 Conclusion

In this paper, we examine the value of humans in an AI + Man model by exploiting the proprietary data from a FinTech company that uses a hybrid AI + Man model to process loan applications from small businesses. We find that the value of human loan officers increases with the use of soft information. The value of human loan officers decreases with agency issues and cognitive constraints. We further find that a performance evaluation policy emphasizing loan quality can induce loan officers to rely more on soft information, partially mitigate agency issues faced by loan officers, but exacerbate the issues caused by cognitive constraints. The results are robust to alternative variable measurements. The study contributes to the AI literature by identifying the conditions under which humans add value. The results also inform FinTech companies and banks about staffing strategies and performance evaluation in an era of accelerating technological integration.

We would like to conclude with a few caveats. First, we focus on the loans approved by loan officers. We do not observe loan applications denied by loan officers. Those approved by the AI system but denied by loan officers might be a profitable opportunity lost for the company. Second, because loan officers make the final decision on loan applications, we do not observe the outcomes that would have happened had the company followed AI recommendations. Thus, we can only estimate the profit based on AI recommendations, and such estimation naturally contains errors. While we do not believe the errors will introduce bias to our analyses, readers should keep this limitation in mind. Lastly, our results might not be generalizable to other settings or across time periods. In particular, AI technology is advancing fast, and companies' reliance on AI might change accordingly. We leave these issues for future research.

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APPENDIX A
Calculation of profit based on loan officers' decisions and AI's recommendations

In this appendix, we use an example to illustrate the calculation of profit of each loan based on the actual loan outcomes and AI's recommendations.

Panel A: Information about the loan and invoice

AI's recommendation: loan amount up to ¥100,000 at an annual interest rate of 15.8%

Loan officer's decision: loan amount up to ¥200,000 at an annual interest rate of 13.8%

Note that while both the AI model and loan officers make decisions at the loan application level, payments occur at the invoice level.

Loan invoice ID: 000LIA2024010000067779

Invoice amount (the amount borrowed): ¥100,000

Borrowing date and time: 2024-01-01 14:04:35

Payment schedule for the invoice:

Payment Date and Time	Repaid Principal	Paid Interest
2024/2/1 8:17	3,678.16	1,066.60
2024/3/1 6:25	3,717.39	1,027.37
2024/4/1 8:00	3,757.04	987.72
2024/5/1 5:41	3,797.11	947.65
2024/6/1 12:28	3,837.61	907.15
2024/6/30 20:00	48,000.00	824.31
2024/7/1 8:22	1,928.79	11.62
2024/7/3 15:27	10,000.00	21.90
2024/8/1 8:23	1,089.80	216.05
2024/9/1 8:37	1,090.46	215.39
2024/10/1 9:22	1,102.09	203.76
2024/11/1 8:40	1,113.85	192.00
2024/12/1 8:28	1,125.73	180.12
2024/12/17 8:41	15,761.97	88.27

Note that interest payments are lower than the accrued interest based on the borrowed amount and the interest rate because of interest rate discounts.

Panel B: Calculation of Profit based on actual cash flows

For each payment, we calculate its present value by using the monthly average Shanghai Interbank Offered Rate (Shibor) for the corresponding period. *Profit* for the invoice based on actual cash flows is calculated as follows:

$$\text{Profit}_{-\text{Man}} = \frac{3{,}678.16 + 1{,}066.6}{(1+\text{Shibor}_{24\text{-}1})^{31/365}} + \frac{3{,}717.39 + 1{,}027.37}{(1+\text{Shibor}_{24\text{-}1})^{31/365}(1+\text{Shibor}_{24\text{-}2})^{29/365}} + \ldots\ldots - 100{,}000 = 5{,}933.38$$

$Shibor_{24\text{-}1}$ refers to the average Shibor rate for January of 2024. Other Shibor variables are defined similarly.

Panel C: Calculation of Profit based on AI's recommendations

To calculate the hypothetical invoice amount and payments based on AI's recommendations, we calculate the adjustment ratio (*Adj_Ratio*) based on AI's recommended amount and loan officer's recommended amount as:

$$\text{Adj\_Ratio} = \text{AI Recommended Amount/Loan Amount Decided by Loan Officer}$$

For the above example: $\text{Adj\_Ratio} = 100{,}000/200{,}000\ = 1/2$

Because many loans have interest rate discount, we calculate the interest discount (*Discount*) for each loan in each month as:

$$\text{Discount}_{\text{m}} = \frac{\text{Paid Interest}_{\text{m}}/\text{Unrepaid\_Amount}_{\text{m}}}{(1+\text{Annual Interest Rate})^{\text{Time}/365}\text{-}1},$$

where *Time* denotes the number of days between the payment timestamp and the previous payment timestamp.

For the above example:

$$\text{Discount}_{24\text{-}1} = \frac{1066.6/100000}{(1+13.8\%)^{31/365}\text{-}1} = 96.61\%$$

$$\text{Discount}_{24\text{-}2} = \frac{1027.37/(100000\text{-}3678.16)}{(1+13.8\%)^{29/365}\text{-}1} = 99.85\%$$

...

We then use the *Adj_Ratio* and *Discount* to calculate the hypothetical (AI-based) borrowed amount, principal payment, and interest payment. Specifically, we calculate the hypothetical AI-based borrowed amount as:

$$\text{AI Invoice Amount} = \text{AI Recommended Amount} \times \textit{Adj\_Ratio},$$

the hypothetical AI-based repaid principal for each month as:

$$\text{AI Repaid Principal}_{\text{m}} = \text{Repaid Principal}_{\text{m}} \times \textit{Adj\_Ratio},$$

and the hypothetical AI-based interest payment for each month as:

$$\text{AI Paid Interest}_{\text{m}} = \text{Unpaid Amount}_{\text{m}} \times \textit{Adj\_Ratio}_m \times [(1+\text{AI Interest Rate})^{\text{Time}/365}\text{-}1] \times \textit{Discount}_m$$

Time denotes the number of days between the current repayment timestamp and the previous payment timestamp.

For the above example:

$$\text{AI Invoice Amount} = 100{,}000 \times \frac{1}{2} = 50{,}000$$

$$\text{AI Paid Principal and Interest}_{24\text{-}1} =$$

$$3{,}678.16 \times \frac{1}{2} + 100{,}000 \times \frac{1}{2} \times [(1+15.8\%)^{\frac{31}{365}}\text{-}1] \times 96.61\% = 2{,}464.99$$

$$\text{AI Paid Principal and Interest}_{24\text{-}2} =$$

$$3{,}717.39 \times \frac{1}{2} + (100{,}000\text{-}3{,}678.16) \times \frac{1}{2} \times [(1+15.8\%)^{\frac{29}{365}}\text{-}1] \times 99.85\% = 2{,}461.58$$

...

We then calculate *Profit* using these values to obtain AI-based profit ($\textit{Profit}_{\_AI}$). For the above example, $\textit{Profit}_{\_AI}$ is calculated as:

$$\text{Profit}_{\_AI}=\frac{2{,}464{,}99}{(1+\text{Shibor}_{24\text{-}1})^{31/365}}+\frac{2{,}461.58}{(1+\text{Shibor}_{24\text{-}1})^{31/365}(1+\text{Shibor}_{24\text{-}2})^{29/365}}+\ldots-50{,}000=3{,}491.05$$

Panel D: Calculation of the deviation in profit

For loans with multiple invoices, we aggregate $Profit_{\_Man}$ and $Profit_{\_AI}$ at the invoice level to obtain the profits at the loan level. We then calculate the deviation in profit of loan officers' decisions from the AI recommendations as the difference in profit at the loan level ($Profit_{\_Man}$– $Profit_{\_AI}$), scaled by the aggregate invoice amount for the loan.

Since the above example has one invoice, the deviation in profit is calculated as:

$$Deviation\_Profit = (5{,}933.38 - 3{,}491.05)/100{,}000 = 2.44\%,$$

$$\text{i.e., } Deviation\_Profit(\%) = 2.44$$

APPENDIX B
Variable Definitions

Variable	Definition
Loan profit variables	
Profit$_{\_Man}$	Actual profit of the loan based on the invoice-level cash flows; please see Appendix A for details of the calculation. For loans with multiple invoices, we aggregate the profit across invoices to obtain the loan-level profit.
Profit$_{\_AI}$	Hypothetical profit of the loan based on AI's recommendation; please see Appendix A for details of the calculation. For loans with multiple invoices, we aggregate the profit across invoices to obtain the loan-level profit.
Deviation_Profit (%)	The difference in profit between loan officers' decision and AI's recommendation, calculated as $100 \times \frac{Profit_{-Man} - Profit_{-AI}}{Invoice\ Amount_{-Man}}$, where *Invoice Amount*$_{\_Man}$ is the total invoice amount, i.e., the total dispensed amount to the borrower (not the approved credit limit). For loans with multiple invoices (multiple drawings from one line of credit), total invoice amount is the sum across invoices.
Loan outcome variables	
Loan Amount$_{\_Man}$	The final loan amount approved by the loan officer.
Interest Rate$_{\_Man}$	The final loan interest rate approved by the loan officer.
Loan Term$_{\_Man}$	The final loan term (in months) approved by the loan officer.
Invoice Amount$_{\_Man}$	The total invoice amount borrowed by the borrower under the loan.
Deviation_Amount	The difference in loan amount between the loan officer's decision and AI's recommendation, scaled by loan amount recommended by AI.
Deviation_Rate (%)	The difference in interest rate between the loan officer's decision and AI's recommendation times 100.
Deviation_Term	The difference in term between the loan officer's decision and AI's recommendation.
Override	An indicator variable that equals one if the loan application is denied by AI but approved by the loan officer, and zero otherwise.
Proxies for soft information	
Comment_Long	An indicator variable that equals one if the length of the loan officer's comment in the justification for loan decision is above the 75th percentile of the sample distribution, and zero otherwise.
Supply_Chain	An indicator variable that equals one if the loan officer's comment in the justification for loan decision mentions the borrower's supply-chain status, and zero otherwise.
Family_Support	An indicator variable that equals one if the loan officer's comment in the justification for loan decision mentions the support for the borrower from his/her family members, and zero otherwise.
Lawsuit_Explanation	An indicator variable that equals one if the loan officer's comment in the justification for loan decision provides explanations for prior or current lawsuits faced by the borrower, and zero otherwise.
Referral	An indicator variable that equals one if the borrower is recommended by existing clients or acquaintances, and zero otherwise.
Proxies for agency issues	
Hometown_Tie	An indicator variable that equals one if the borrower is from the same province as the loan officer, and zero otherwise.
Lower_Rate	An indicator variable that equals one if the approved interest rate by loan officer is the same as or lower than the interest rate recommended by the customer officer who handles the loan application, and zero otherwise. For

	loans without recommended interest rates from customer officers, *Lower_Rate* is set as zero.
Peer_Pressure	An indicator variable that equals one if, at the time when the loan is approved, the number of loans approved by the loan officer from the beginning of the day is lower than the average number of loans approved by all loan officers for the same period of the previous week, and zero otherwise.
FridayEOD	An indicator variable that equals one if the loan is approved at the end of Friday (between 4pm and 5pm), and zero otherwise.
Proxies for cognitive constraints	
Multi_Loan	An indicator variable that equals one if the borrower has unpaid loans from other financial institutions at the time of loan application, and zero otherwise.
Ind_Experience_L	An indicator variable that equals one if the borrower is in an industry from which the loan officer has approved fewer than 10 loan applications in the previous month, and zero otherwise.
Peak_Hour	An indicator variable that equals one if the loan is approved during daily peak approval hours (i.e., 10-11am and 4-5pm), and zero otherwise.
Before_Dinner	An indicator variable that equals one if the time of loan approval is right before dinner time (i.e., 4:30~5pm), and zero otherwise.

APPENDIX C
Correlation Matrix

This table reports the correlation matrix for the variables used in the main analysis. All variables are defined in Appendix B. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Comment_Long (1)	1											
Supply_Chain (2)	0.079***	1										
Family_Support (3)	0.160***	0.024***	1									
Lawsuit_Explanation (4)	0.177***	0.037***	0.041***	1								
Referral (5)	0.050***	0.016**	0.000	-0.002	1							
Hometown_Tie (6)	0.056***	0.036***	0.037***	0.003	0.031***	1						
Lower_Rate (7)	0.041***	0.010	0.007	-0.004	-0.009	0.031***	1					
Peer_Pressure (8)	0.014*	0.001	-0.011	-0.001	-0.001	0.001	0.012	1				
Friday_EOD (9)	-0.012	-0.020***	-0.013*	-0.010	0.010	-0.003	-0.007	-0.034***	1			
Multi_Loan (10)	0.004	0.010	0.004	0.007	-0.010	-0.001	-0.092***	0.026***	0.004	1		
Ind_Experience_L (11)	0.009	0.013*	0.007	0.022***	-0.018**	0.021***	0.031***	0.031***	0.014*	0.024***	1	
Peak_Hour (12)	-0.019***	-0.005	-0.017**	-0.021***	0.006	-0.005	-0.008	0.005	0.283***	-0.009	-0.015**	1
Before_Dinner (13)	-0.014*	-0.001	-0.023***	-0.011	0.004	0.003	-0.009	-0.010	0.283***	-0.005	-0.006	0.503***

FIGURE 1
Distribution of the Deviation in Profit

This figure depicts the distribution of the deviation in profit (*Deviation_Profit*). The x-axis indicates the value of *Deviation_Profit*, with intervals of 1%. The y-axis indicates the number of loans with the value in each interval. The red dot line indicates the zero interval, i.e., *Deviation_Profit* (%) in (-0.5,0.5).

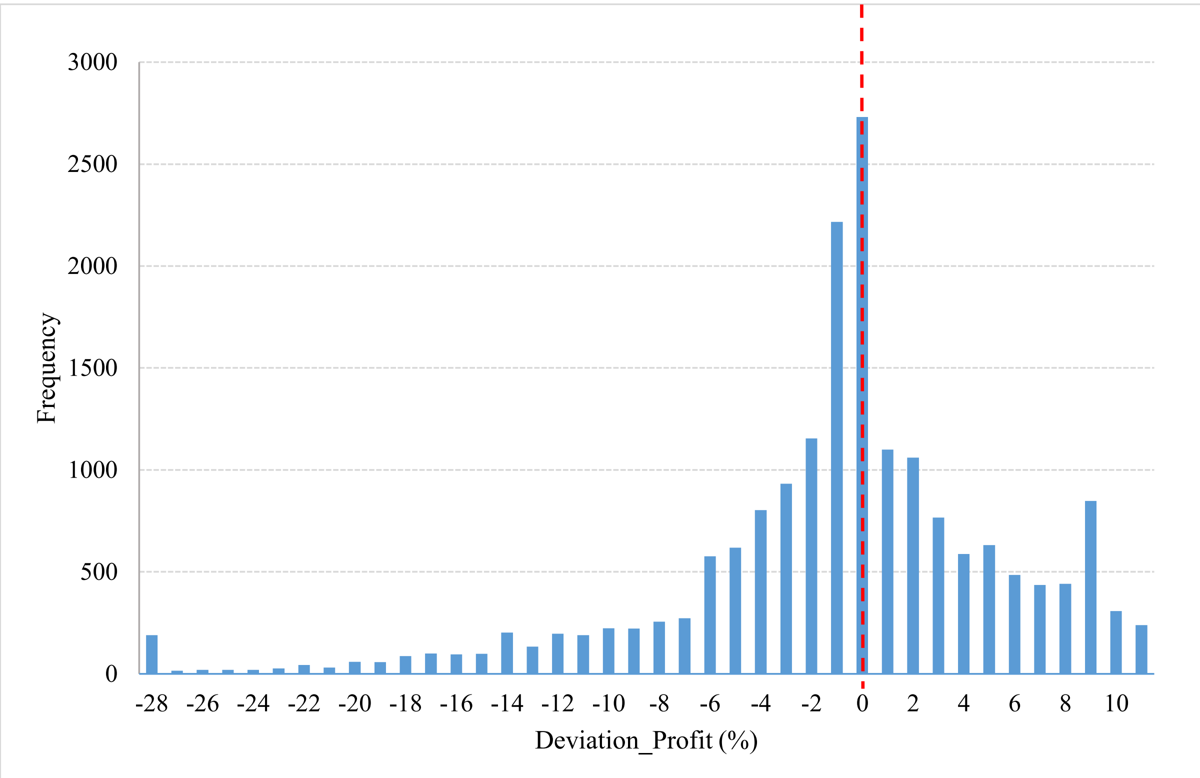

TABLE 1
Sample Selection

This table reports the sample selection process for the main analysis. The final sample consists of 18,490 loan observations from 2024.

	Obs.
All loans approved in 2024	28,137
Less:	
Loans that have not matured at the time of data collection	(6,730)
Loans with missing values on loan outcomes and other variables	(2,706)
Loans approved by loan officers who approved fewer than 100 loans in 2024	(52)
Singleton observations	(159)
Final sample	18,490

TABLE 2

Descriptive Statistics on Loan Outcomes and Proxies for Soft Information, Agency Issues, and Cognitive Constraints

This table reports descriptive statistics on loan outcomes and proxies for soft information, agency issues, and cognitive constraints. Panel A reports the means and standard deviations of loan outcomes (loan amount, interest rate, and loan term) based on AI recommendations and loan officers' decisions, and the difference in means between AI recommendations and loan officers' decisions. Panel B reports descriptive statistics on the proxies for soft information, agency issues, and cognitive constraints. Appendix B provides variable definitions. The sample consists of 18,490 loan observations from 2024.

Panel A: Loan outcomes based on AI recommendations and loan officers' decisions

	AI recommendations		Loan officers' decisions		Difference in mean	
	Mean (1)	Std. (2)	Mean (3)	Std. (4)	(3) − (1)	*t*-statistics
Loan Amount (CNY)	126,947	97,540	161,846	50,632	34,899***	46.21
Interest Rate (%)	18.15	1.60	14.51	2.54	-3.64***	-170.00
Loan Term (month)	16.58	6.28	24.62	11.37	8.04***	83.99

Panel B: Descriptive statistics on proxies for soft information, agency issues, and cognitive constraints

	Mean	Std.	Q1	Median	Q3
Comment_Long	0.269	0.444	0	0	1
Supply_Chain	0.024	0.153	0	0	0
Family_Support	0.077	0.267	0	0	0
Lawsuits_Explanation	0.083	0.276	0	0	0
Referral	0.343	0.475	0	0	1
Hometown_Tie	0.050	0.217	0	0	0
Lower_Rate	0.173	0.378	0	0	0
Peer_Pressure	0.551	0.497	0	1	1
Friday_EOD	0.029	0.162	0	0	0
Multi_Loan	0.383	0.486	0	0	1
Ind_Experience_L	0.216	0.411	0	0	0
Peak_Hour	0.256	0.436	0	0	1
Before_Dinner	0.080	0.271	0	0	0

TABLE 3
Descriptive Statistics on Deviation in Profit

This table reports descriptive statistics on deviation in loan profit and loan outcomes. Panel A reports the means and standard deviations of *Profit* based on AI recommendations and loan officers' decisions, and the difference in means between the two. Panel B reports descriptive statistics for the deviation in profit, loan amount, interest rate, and term, and the likelihood of loan officers overriding AI's recommendations of loan denial. Appendix B provides variable definitions. The sample consists of 18,490 loan observations from 2024.

Panel A: Profit based on AI recommendations and loan officers' decisions

	AI recommendations		Loan officers' decisions		Difference in Mean	
	Mean (1)	Std. (2)	Mean (3)	Std. (4)	(3) − (1)	*t*-statistics
Profit (CNY)	13,376.67	13,193.88	13,153.45	8,297.73	-223.22***	-2.63

Panel B: Descriptive statistics on the deviation in profit and loan outcomes

Variable	Mean	Std.	Q1	Median	Q3
Deviation_Profit (%)	-0.495	6.776	-2.915	0.020	3.162
Deviation_Amount	2.134	3.478	-0.100	0.333	4
Deviation_Rate (%)	-3.641	2.893	-5.7	-4	-1.1
Deviation_Term	8.043	13.022	0	12	24
Override	0.609	0.488	0	1	1

TABLE 4
Determinants of Deviation in Profit

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the difference in loan outcomes—amount (*Deviation_Amount*), interest rate (*Deviation_Rate*), loan term (*Deviation_Term*)—and the likelihood of loan officers overriding AI's recommendations (*Override*). Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Dependent variable =	*Deviation_Profit (%)*					
	(1)	(2)	(3)	(4)	(5)	Shapley values
Deviation_Amount	1.231***				1.258***	89.03%
	(65.56)				(63.74)	
Deviation_Rate (%)		0.277***			0.444***	5.58%
		(12.14)			(27.15)	
Deviation_Term			0.029***		0.029***	0.71%
			(6.23)		(6.96)	
Override				0.588***	0.239**	0.27%
				(4.70)	(2.56)	
Month FE	Yes	Yes	Yes	Yes	Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	
Loan Officer FE	Yes	Yes	Yes	Yes	Yes	
Obs.	18,490	18,490	18,490	18,490	18,490	
Adj. R^2	0.380	0.023	0.014	0.013	0.411	

TABLE 5
Soft Information and Deviation in Profit

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for soft information used by loan officers. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Dependent variable =	*Deviation_Profit (%)*				
	(1)	(2)	(3)	(4)	(5)
Comment_Long	0.517***				
	(3.18)				
Supply_Chain		0.506**			
		(1.97)			
Family_Support			0.858***		
			(7.37)		
Lawsuit_Explanation				0.596***	
				(2.67)	
Referral					0.219**
					(2.48)
Month FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes
Obs.	18,490	18,490	18,490	18,490	18,490
Adj. R^2	0.012	0.011	0.012	0.012	0.011

TABLE 6
Agency Issues and Deviation in Profit

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for agency issues faced by loan officers. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Dependent variable =	*Deviation_Profit (%)*			
	(1)	(2)	(3)	(4)
Hometown_Tie	-1.050***			
	(-4.10)			
Lower_Rate		-0.933***		
		(-6.22)		
Peer_Pressure			-0.704***	
			(-5.23)	
Friday_EOD				-0.630**
				(-2.24)
Month FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Obs.	18,490	18,490	18,490	18,490
Adj. R^2	0.012	0.012	0.014	0.011

TABLE 7
Cognitive Constraints and Deviation in Profit

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for cognitive constraints faced by loan officers, with Panel A on the complexity of loan applications and Panel B on loan officers' mental fatigue. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Panel A: Loan application complexity and deviation in profit

Dependent variable =	*Deviation_Profit (%)*	
	(1)	(2)
Multi_Loan	-1.388***	
	(-9.37)	
Ind_Experience_L		-0.676***
		(-4.94)
Month FE	Yes	Yes
Industry FE	Yes	Yes
Loan Officer FE	Yes	Yes
Obs.	18,490	18,490
Adj. R^2	0.021	0.012

Panel B: Mental fatigue and deviation in profit

Dependent variable =	*Deviation_Profit (%)*	
	(1)	(2)
Peak_Hour	-0.243**	
	(-2.46)	
Before_Dinner		-0.372**
		(-2.03)
Month FE	Yes	Yes
Industry FE	Yes	Yes
Loan Officer FE	Yes	Yes
Obs.	18,490	18,490
Adj. R^2	0.011	0.011

TABLE 8
Analyses of the Deviation in Profit Separately for Loans Approved in the First and Second Half of 2024

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for soft information used by loan officers (Panel A), agency issues faced by loan officers (Panel B), and cognitive constraints experienced by loan officers (Panel C), separately for loans approved in the first half of 2024 and in the second half of the year. For brevity, the table only reports the coefficient and *t*-statistics for the variables of interest. The bottom of each panel reports the differences in coefficients between the two subsamples and the corresponding *p*-values. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Panel A: Soft information and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*				
Soft information proxy =	*Comment_Long*	*Supply_Chain*	*Family_Support*	*Lawsuit_Explanation*	*Referral*
Loans approved in January-June of 2024 (N = 11,374)					
Soft information proxy (1)	0.398**	0.654	0.407*	0.424*	0.317***
	(2.18)	(1.62)	(1.70)	(1.71)	(3.09)
Loans approved in July-December of 2024 (N = 7,113)					
Soft information proxy (2)	0.649***	0.354	1.343***	0.840***	0.084
	(3.15)	(1.12)	(6.07)	(2.93)	(0.61)
Difference in coef.: (2) – (1)	0.251*	-0.300	0.936***	0.416*	-0.133
(p-value)	(0.10)	(0.27)	(0.01)	(0.08)	(0.23)

TABLE 8 (cont'd)

Panel B: Agency issues and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Agency issue proxy =	*Hometown_Tie*	*Lower_Rate*	*Peer_Pressure*	*Friday_EOD*
Loans approved in January-June of 2024 (N = 11,374)				
Agency issue proxy (1)	-1.575***	-1.579***	-0.546***	-0.912**
	(-5.46)	(-6.84)	(-3.32)	(-2.04)
Loans approved in July-December of 2024 (N = 7,113)				
Agency issue proxy (2)	-0.402	-0.591***	-1.013***	-0.230
	(-1.04)	(-4.36)	(-6.29)	(-0.51)
Difference in coef.: (2) – (1)	1.173***	0.987***	-0.467**	0.682*
(p-value)	(0.00)	(0.00)	(0.03)	(0.07)

Panel C: Cognitive constraints and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Cognitive constraint proxy =	*Multi_Loan*	*Ind_Experience_L*	*Peak_Hour*	*Before_Dinner*
Loans approved in January-June of 2024 (N = 11,374)				
Cognitive constraint proxy (1)	-1.009***	-0.428***	0.015	-0.273
	(-6.13)	(-2.76)	(-0.12)	(-1.06)
Loans approved in July-December of 2024 (N = 7,113)				
Cognitive constraint proxy (2)	-2.033***	-1.335***	-0.653***	-0.531**
	(-12.75)	(-4.10)	(-3.62)	(-2.47)
Difference in coef.: (2) – (1)	-1.024***	-0.907***	-0.638***	-0.258
(p-value)	(0.00)	(0.00)	(0.00)	(0.25)

TABLE 9
Analyses of the Deviation in Profit Separately for Override and Non-override Samples

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for soft information used by loan officers (Panel A), agency issues faced by loan officers (Panel B), and cognitive constraints experienced by loan officers (Panel C), separately for the override sample, where loan officers override AI's loan denial recommendation by approving the loan applications, and the non-override sample, where loan officers agree with AI's loan approval recommendations. For brevity, the table only reports the coefficient and *t*-statistics for the variables of interest. The bottom of each panel reports the difference in coefficients between the two subsamples and the corresponding *p*-values. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Panel A: Soft information and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*				
Soft information proxy =	*Comment_Long*	*Supply_Chain*	*Family_Support*	*Lawsuit_Explanation*	*Referral*
Non-override sample (N = 7,227)					
Soft information proxy (1)	0.467*	0.409	0.611**	0.164	0.164
	(1.86)	(0.86)	(2.20)	(0.62)	(1.08)
Override sample (N = 11,257)					
Soft information proxy (2)	0.657***	0.650	1.067***	1.066***	0.241***
	(3.62)	(1.41)	(5.96)	(5.11)	(2.69)
Difference in coef.: (2) – (1)	0.190	0.241	0.456*	0.902***	0.077
(p-value)	(0.21)	(0.38)	(0.06)	(0.00)	(0.41)

TABLE 9 (cont'd)

Panel B: Agency issues and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Agency issue proxy =	*Hometown_Tie*	*Lower_Rate*	*Peer_Pressure*	*Friday_EOD*
Non-override sample (N = 7,227)				
Agency issue proxy (1)	-0.488	-1.425***	-0.691***	-0.751
	(-1.16)	(-5.13)	(-3.83)	(-1.31)
Override sample (N = 11,257)				
Agency issue proxy (2)	-1.619***	-0.689***	-0.711***	-0.534*
	(-5.20)	(-4.88)	(-4.85)	(-1.78)
Difference in coef.: (2) – (1)	-1.131**	0.736***	-0.020	0.217
(p-value)	(0.03)	(0.01)	(0.40)	(0.36)

Panel C: Cognitive constraints and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Cognitive constraint proxy =	*Multi_Loan*	*Ind_Experience_L*	*Peak_Hour*	*Before_Dinner*
Non-override sample (N = 7,227)				
Cognitive constraint proxy (1)	-1.084***	-0.345	-0.288	-0.234
	(-6.26)	(-1.45)	(-1.21)	(-0.59)
Override sample (N = 11,257)				
Cognitive constraint proxy (2)	-1.596***	-0.836***	-0.238	-0.480**
	(-7.78)	(-3.91)	(-1.51)	(-2.08)
Difference in coef.: (2) – (1)	-0.512***	-0.491**	0.050	-0.246
(p-value)	(0.00)	(0.05)	(0.39)	(0.22)

TABLE 10
The Relative Importance of Soft Information, Agency Issues, and Cognitive Constraints

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for soft information used by loan officers, agency issues faced by loan officers, and cognitive constraints experienced by loan officers in one regression. Appendix B provides variable definitions. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Dependent variable =		*Deviation_Profit (%)*	
		Coefficient (t-statistics)	Shapley value
Soft information	*Comment_Long*	0.487***	3.22%
		(3.12)	
	Supply_Chain	0.436*	0.66%
		(1.71)	
	Family_Support	0.791***	3.02%
		(6.27)	
	Lawsuit_Explanation	0.418*	0.95%
		(1.92)	
	Referral	0.236***	1.18%
		(2.66)	
Agency issues	*Hometown_Tie*	-1.101***	3.65%
		(-4.36)	
	Lower_Rate	-1.123***	8.37%
		(-6.84)	
	Peer_Pressure	-0.635***	5.82%
		(-5.21)	
	Friday_EOD	-0.459	0.43%
		(-1.62)	
Cognitive constraints	*Multi_Loan*	-1.470***	30.11%
		(-9.84)	
	Industry_Experience	-0.625***	1.84%
		(-4.53)	
	Peak_Hour	-0.140	0.61%
		(-1.41)	
	Before_Dinner	-0.170	0.55%
		(-0.94)	
Month FE		Yes	
Industry FE		Yes	
Loan Officer FE		Yes	
Obs.		18,490	
Adj. R^2		0.031	

TABLE 11
Analyses of the Deviation in Profit Using Alternative Interest Rate for AI-based Profit

This table reports the regression results of the deviation in profit (*Deviation_Profit*) on the proxies for soft information used by loan officers (Panel A), agency issues faced by loan officers (Panel B), and cognitive constraints faced by loan officers (Panel C). For brevity, the table only reports the coefficient and *t*-statistics for the variables of interest. Appendix B provides variable definitions; for the calculation of *Profit_AI*, we use the average interest rate charged on loans approved by both AI and loan officers in the previous month. Intercepts are included but not tabulated. The sample includes 18,490 loan observations in 2024. The *t*-statistics in parentheses are based on standard errors adjusted for clustering at the loan officer level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, based on two-sided tests.

Panel A: Soft information and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*				
Soft information proxy =	*Comment_Long*	*Supply_Chain*	*Family_Support*	*Lawsuit_Explanation*	*Referral*
Soft information proxy	0.365**	0.380	0.754***	0.413**	0.219***
	(2.43)	(1.52)	(6.39)	(2.02)	(2.70)

Panel B: Agency issues and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Agency issue proxy =	*Hometown_Tie*	*Lower_Rate*	*Peer_Pressure*	*Friday_EOD*
Agency issue proxy	-0.998***	-0.959***	-0.638***	-0.734***
	(-4.44)	(-7.23)	(-5.30)	(-2.77)

Panel C: Cognitive constraints and the deviation in profit

Dependent variable =	*Deviation_Profit (%)*			
Cognitive constraint proxy =	*Multi_Loan*	*Ind_Experience_L*	*Peak_Hour*	*Before_Dinner*
Cognitive constraint proxy	-1.465***	-0.609***	-0.233***	-0.272*
	(-12.07)	(-4.81)	(-2.68)	(-1.69)