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Income Perception, Interest Rate Perception, and Digital Microfinance Adoption: Micro-Enterprise Credit Decision-Making in Indonesia's KUR Program

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ABSTRACT

Purpose. This study examines the influence of income perception and interest rate perception on Kredit Usaha Rakyat (KUR) uptake decisions among micro-entrepreneurs in Kecamatan Palaran, Samarinda, East Kalimantan, Indonesia, within the broader context of the ongoing digitalization of government-subsidized microfinance services.

However, prior studies on microcredit in Indonesia have largely examined income and interest rate effects in conventional, branch-based lending, with limited evidence on how these perceptions operate within digitalized, government-subsidized schemes such as KUR and in underrepresented locations like Palaran. This paper addresses this gap by analysing income and interest rate perceptions in the context of digitally mediated KUR uptake among micro-entrepreneurs in Palaran, East Kalimantan.

Design/Methodology/Approach. A quantitative cross-sectional survey was conducted with 50 micro-enterprise owners selected through purposive sampling. Data were collected using a structured questionnaire comprising 12 Likert-scale items measuring income perception, interest rate perception, and KUR uptake decisions. A dual analytical approach was employed: SmartPLS 3.0 for measurement model validation (convergent validity and reliability) and SPSS 25.0 for hypothesis testing via multiple linear regression analysis, including F-tests, t-tests, and coefficient of determination (R^2).

Findings. Income perception does not exert a statistically significant partial effect on KUR uptake decisions (B = 0.214,

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p = 0.072), while interest rate perception has a significant positive effect (B = 0.201, p = 0.046). Jointly, both variables significantly predict KUR uptake decisions (F = 22.621, p = 0.000), explaining 49.9% of the variance. The remaining 50.1% suggests the presence of additional determinants, potentially including digital financial literacy, platform usability, and digital trust.

Research Implications. The findings challenge the assumption that income perception is a universal predictor of microcredit behavior and suggest that digital financial platforms may diminish the salience of income-based credit barriers while amplifying the role of interest rate transparency through digital information mechanisms.

Practical Implications. Banks and fintech companies distributing KUR should prioritize transparent interest rate display, interactive loan simulators, and AI-powered chatbot advisory services on digital platforms. Policymakers should integrate digital financial literacy into national inclusion strategies.

Originality/Value. This study bridges classical microfinance theory with the emerging discourse on digital financial inclusion and AI-driven credit assessment, offering empirical evidence from an underrepresented Indonesian geographic context and proposing an AI-Enhanced KUR Distribution Framework for future policy design.

1. INTRODUCTION

1.1 Background and Context

Micro, small, and medium enterprises (MSMEs) constitute the backbone of Indonesia's economy, contributing approximately 61% of the nation's gross domestic product and absorbing over 97% of the total workforce (Ministry of Cooperatives and SMEs, 2023). Despite their macroeconomic significance, micro-enterprises—the smallest segment within the MSME ecosystem—face persistent challenges in accessing formal financial services, particularly credit facilities that are essential for business expansion and sustainability (Tambunan, 2019; Yoshino & Taghizadeh-Hesary, 2018). Recognizing this structural impediment, the Indonesian government introduced the Kredit Usaha Rakyat (KUR), or People's Business Credit, as a government-subsidized microloan program designed to provide affordable financing to micro and small enterprises that lack sufficient collateral or credit history for conventional bank lending (Regulation of the Coordinating Minister for Economic Affairs No. 8 of 2015).

The KUR program has undergone significant transformation since its inception, evolving from a purely branch-based, paper-intensive lending mechanism to an increasingly digitalized financial service. In recent years, the Indonesian government has actively promoted the digital distribution of KUR through partnerships with commercial banks, fintech platforms, and digital marketplaces, enabling micro-entrepreneurs to apply for and manage

credit facilities through mobile banking applications and online portals (Bank Indonesia, 2023). This digital transformation has fundamentally altered the informational landscape surrounding microcredit, providing borrowers with unprecedented access to interest rate comparisons, loan simulators, and real-time application tracking—features that were previously unavailable in the traditional lending environment.

While national policy initiatives and regulatory reforms have expanded the digital distribution of KUR, many micro-entrepreneurs still face uncertainty about their own repayment capacity and the affordability of subsidized interest rates. Consequently, understanding how income and interest rate perceptions shape KUR uptake decisions in this evolving environment becomes a central empirical question of this study.

1.2 The Digital Transformation of KUR

The digitalization of KUR distribution represents a broader trend in financial inclusion strategies across emerging economies. Indonesia's national financial inclusion strategy, which targets 90% financial inclusion by 2024, has explicitly prioritized digital channels as the primary vehicle for reaching underserved micro-enterprises in peripheral urban and rural areas (Otoritas Jasa Keuangan [OJK], 2022). Digital KUR platforms have introduced several innovative features, including algorithm-assisted eligibility screening, automated document verification, and digital signature capabilities, which collectively reduce transaction costs and processing times for both lenders and borrowers (Wulandari et al., 2022).

Furthermore, the emergence of artificial intelligence (AI) and machine learning applications in credit assessment has begun to reshape how banks evaluate the creditworthiness of micro-enterprises. AI-driven credit scoring models, which incorporate alternative data sources such as mobile phone usage patterns, digital payment histories, and social media footprints, have the potential to reduce information asymmetry between lenders and micro-borrowers who lack traditional credit documentation (Bazarbash, 2019; Frost et al., 2019). While these technologies are still in the early stages of deployment for KUR specifically, they represent the direction of Indonesia's microfinance infrastructure and provide an important contextual backdrop for understanding contemporary microcredit decision-making behavior.

Although digital platforms and AI-based credit assessment provide an important contextual backdrop for contemporary KUR distribution, these technological aspects are not modeled as explicit variables in this study. Instead, they are treated as part of the institutional environment within which traditional economic perceptions of income and interest rates influence micro-entrepreneurs' credit decisions

1.3 Research Gap

A substantial body of literature has examined the determinants of microcredit uptake in developing economies, with income levels and interest rates consistently identified as significant predictors of borrowing decisions (Demirgüç-Kunt et al., 2018; Karlan & Zinman, 2019). However, the majority of these studies were conducted within traditional lending frameworks that preceded the current wave of financial digitalization. Consequently, there remains a critical gap in understanding how the perceptions of income adequacy and interest rate affordability operate within the context of digitalized microfinance services, particularly government-subsidized programs such as KUR.

Moreover, while several studies have investigated the adoption of digital financial services in Indonesia (Setiawan et al., 2021; Trinugroho et al., 2021), few have specifically examined how the digitalization of KUR intersects with the traditional economic determinants

of microcredit decision-making. The interaction between borrowers' subjective economic perceptions and the evolving digital environment in which credit decisions are made represents an underexplored area that warrants empirical investigation.

Additionally, there is a notable geographic bias in existing research, with most studies focusing on major urban centers such as Jakarta, Surabaya, and Bandung, thereby overlooking the unique dynamics of micro-enterprise credit behavior in emerging urban districts such as Kecamatan Palaran in East Kalimantan, where the interplay between traditional economic activities and digital financial infrastructure is particularly pronounced.

1.4 Research Objectives and Questions

This study aims to examine the influence of income perception and interest rate perception on KUR uptake decisions among micro-entrepreneurs in Kecamatan Palaran, Samarinda, East Kalimantan, within the broader context of Indonesia's ongoing digitalization of microfinance services. Specifically, this research addresses the following questions:

1. Does income perception significantly influence KUR uptake decisions among micro-entrepreneurs in the context of digitalized financial services?
2. Does interest rate perception significantly influence KUR uptake decisions among micro-entrepreneurs in the context of digitalized financial services?
3. Do income perception and interest rate perception simultaneously influence KUR uptake decisions?

1.5 Contribution Statement

This study makes three distinct contributions to the literature. First, it provides empirical evidence on the role of traditional economic perceptions—income and interest rates—in microcredit decision-making within a rapidly digitalizing financial environment, thereby bridging the gap between classical microfinance literature and the emerging digital finance discourse. Second, it offers insights from an understudied geographic context (Kecamatan Palaran, East Kalimantan), contributing to the diversification of the evidence base beyond Indonesia's major metropolitan areas. Third, by situating the empirical findings within the framework of digital financial inclusion and AI-driven credit assessment, this study generates forward-looking implications for policymakers, banking institutions, and technology developers engaged in the digital transformation of government-subsidized microloan programs in emerging economies.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Government-Subsidized Microcredit Programs in Developing Economies

Government-subsidized microcredit programs have long been recognized as critical instruments for promoting financial inclusion and supporting micro-enterprise development in emerging economies (Banerjee et al., 2015; Morduch, 1999). Indonesia's KUR program, established through Presidential Instruction No. 6 of 2007 and subsequently regulated by the Coordinating Minister for Economic Affairs (Regulation No. 8 of 2015), provides subsidized-interest loans of up to IDR 500 million to MSMEs that are considered productive and feasible but lack the collateral required for conventional bank financing. As of 2024, the KUR interest rate has been set at approximately 6–7% per annum, substantially below commercial lending rates, making it one of the most accessible formal credit instruments for Indonesian micro-enterprises (Ministry of Finance, 2023).

Comparable programs exist across the developing world. India's Pradhan Mantri MUDRA Yojana (PMMY) provides collateral-free loans to micro and small enterprises through a similar government-guarantee mechanism (Nayak & Mahapatra, 2021). In Bangladesh, the Grameen Bank model pioneered group-based microlending that has since been replicated across South and Southeast Asia (Yunus, 2007). Kenya's mobile-first approach to microfinance, exemplified by M-Shwari and other M-Pesa-integrated lending products, demonstrates how digital infrastructure can fundamentally reshape microcredit access patterns (Suri & Jack, 2016). These international comparisons provide a valuable lens through which to interpret the dynamics of KUR uptake in Indonesia.

2.2 Digital Financial Inclusion and Fintech Lending

Digital financial inclusion refers to the use of digital technologies to provide financial services to populations that are underserved by traditional financial institutions (Ozili, 2018; Demirgüç-Kunt et al., 2018). The World Bank's Global Findex Database (2021) documents a dramatic acceleration in digital financial service adoption across developing economies, with Indonesia experiencing a 25-percentage-point increase in account ownership between 2014 and 2021, largely driven by mobile money and digital banking platforms.

The integration of financial technology (fintech) into microlending has introduced several transformative dynamics. First, digital platforms reduce transaction costs for both borrowers and lenders by eliminating the need for physical branch visits and paper-based documentation (Philippon, 2016). Second, algorithmic credit assessment—increasingly powered by machine learning and artificial intelligence—enables lenders to evaluate borrowers using non-traditional data sources, potentially expanding credit access to previously excluded populations (Berg et al., 2020; Jagtiani & Lemieux, 2019). Third, digital platforms enhance information transparency by providing borrowers with real-time access to loan terms, interest rate comparisons, and repayment simulators, thereby reducing the information asymmetry that has historically characterized microfinance markets (Gabor & Brooks, 2017). Research in Indonesia's digital platforms has demonstrated that key factors such as user interface quality, personalized content recommendations, platform responsiveness, and security features significantly influence customer experience and engagement, which in turn shape transaction decisions (Felix & Rembulan, 2023). Digital transformation can enhance the customer experience, which in turn strengthens customer engagement and loyalty in digital service settings (Felix & Rembulan, 2023b).

In the context of KUR, the Indonesian government has progressively mandated the digital channeling of microcredit through state-owned and commercial banks' mobile applications, as well as through partnerships with e-commerce platforms such as Tokopedia and Bukalapak (OJK, 2022). This digitalization has implications for how micro-entrepreneurs perceive and respond to the economic parameters of credit, including income requirements and interest rates, as information that was previously opaque becomes increasingly accessible and comparable through digital interfaces.

2.3 AI-Driven Credit Scoring and Its Implications for Microfinance

Artificial intelligence and machine learning have increasingly been applied to credit scoring in both developed and developing financial markets. Traditional credit scoring models rely predominantly on formal financial data such as bank account histories, tax records, and collateral valuations—information that is often unavailable for micro-entrepreneurs in the informal sector (Bazarbash, 2019). AI-driven alternative credit scoring addresses this limitation by incorporating a wider range of data inputs, including mobile phone usage

patterns, digital payment behaviors, social network characteristics, and even psychometric assessments (Björkegren & Grissen, 2020; Berg et al., 2020).

Several Indonesian banks and fintech companies have begun implementing AI-based credit assessment systems for microenterprise lending. For instance, Bank Rakyat Indonesia (BRI), the largest distributor of KUR, has invested in machine learning models to improve the accuracy and efficiency of its credit evaluation processes (BRI Annual Report, 2023). While these AI systems are not yet universally applied to all KUR applications, their growing deployment represents a significant contextual shift in the microfinance landscape—one that may alter the relative importance of traditional determinants such as perceived income in borrowing decisions.

The relevance of AI-driven credit scoring to this study lies not in its direct measurement but in its role as an environmental factor that shapes the information ecosystem within which micro-entrepreneurs make credit decisions. As AI systems increasingly determine creditworthiness based on behavioral and transactional data rather than self-reported income, the salience of income perception as a psychological driver of credit uptake may diminish—a hypothesis that aligns with this study's empirical findings, as discussed in subsequent sections.

Accordingly, while the discussion of digital financial inclusion and AI-driven credit scoring frames the broader transformation of Indonesia's microfinance landscape, the empirical analysis in this paper focuses narrowly on income and interest rate perceptions as the primary determinants of KUR uptake decisions.

2.4 Consumer Decision-Making in Financial Services

Consumer behavior theory provides the foundational framework for understanding microcredit decision-making. According to Balqiah and Setyowardhani (2014), consumer behavior encompasses the processes through which individuals or groups search for, purchase, use, evaluate, and dispose of products and services to satisfy their needs. In the context of credit decisions, this process involves evaluating the perceived costs (interest rates, administrative fees) against the perceived benefits (business expansion, income growth) of borrowing.

The theory of utility, rooted in neoclassical economics, posits that individuals make rational decisions aimed at maximizing their utility or satisfaction (Priyono & Ismail, 2017). Applied to microcredit, utility maximization theory suggests that micro-entrepreneurs will opt for KUR when the expected utility from credit utilization—measured in terms of anticipated business growth—exceeds the disutility of borrowing costs. However, behavioral economics has challenged the strict rationality assumption, demonstrating that cognitive biases, heuristics, and framing effects significantly influence financial decision-making (Kahneman, 2011; Thaler & Sunstein, 2008).

The digital environment introduces additional behavioral dimensions. Digital nudging—the use of interface design elements to guide user behavior on digital platforms—has been shown to influence financial decisions, including loan uptake, savings behavior, and investment choices (Benartzi & Thaler, 2013; Mirsch et al., 2017). Moreover, the adoption of technology in service delivery has been demonstrated to enhance customer experience and satisfaction, which directly influences user behavior and decision-making in digital platforms (Felix et al., 2024). For micro-entrepreneurs accessing KUR through digital platforms, the design of loan application interfaces, the presentation of interest rate information, and the availability of automated loan calculators may all function as digital nudges that shape credit decision-making in ways that traditional branch-based lending does not.

2.5 Income Perception and Credit Decisions

Income perception refers to an individual's subjective assessment of their earnings—whether from primary business activities, supplementary income sources, or other economic activities—and its adequacy for meeting current and future financial obligations (Suroto, 2000; Ilza, 2023). In the context of microcredit, income perception operates as a proxy for self-assessed repayment capacity: micro-entrepreneurs who perceive their income as sufficient or growing may feel more confident in their ability to service loan obligations, thereby increasing their propensity to borrow.

Empirical evidence on the relationship between income perception and credit uptake is mixed. Several studies have reported a significant positive relationship, suggesting that higher perceived income increases borrowing confidence and credit demand (Hutapea & Dewi, 2021; Ilza, 2023). However, other studies have found non-significant or weak effects, indicating that income perception may be overshadowed by other factors such as credit accessibility, financial literacy, or social influence in specific contexts (Saparuddin, 2022; Karyani, 2022).

The non-significance of income perception in certain contexts has been attributed to structural factors that decouple income from credit access. In digital lending environments, for instance, the availability of small-ticket loans with flexible repayment terms may reduce the relevance of perceived income as a borrowing determinant, as borrowers can access credit amounts that are calibrated to their immediate capacity rather than their overall income level (Suri & Jack, 2016). This interpretation is particularly relevant in the context of digitalized KUR, where online platforms may democratize access by lowering the perceived income threshold for credit participation.

2.6 Interest Rate Perception and Credit Decisions

Interest rate perception refers to the borrower's subjective evaluation of the cost of borrowing—specifically, whether the interest rate charged on a loan is perceived as fair, affordable, and proportionate to the expected benefits of the credit facility (Kasmir, 2010; Warjiyo & Solikin, 2003). In classical monetary economics, interest rates function as the primary price mechanism for credit, with higher rates expected to reduce borrowing demand (Keynesian investment theory) and lower rates expected to stimulate credit uptake (Priyono & Ismail, 2017).

Empirical evidence generally supports the significance of interest rate perception in credit decision-making. Rahmawati and Widodo (2023) found that interest rates, along with service quality and credit procedures, significantly influenced credit uptake decisions at Bank Rembang. Similarly, Tobing and Herman (2020) reported a positive and significant relationship between interest rates and credit decisions at a financing company in Batam, suggesting that borrowers who perceive interest rates as reasonable are more inclined to proceed with loan applications.

The digital context amplifies the role of interest rate perception through enhanced information transparency. Digital platforms enable borrowers to compare interest rates across multiple lenders, access real-time loan simulators, and receive personalized rate estimates—features that make interest rate information more salient and actionable (Philippon, 2016; Buchak et al., 2018). For KUR, which offers a government-subsidized rate of approximately 6–7%, the digital presentation of this relatively low rate in comparison to commercial alternatives may serve as a powerful motivator for credit uptake.

2.7 The Digital Context as a Moderating Environment

While this study does not directly measure digital variables, it is theoretically important to conceptualize the digital environment as a moderating context that shapes how traditional economic perceptions translate into credit decisions. Two prominent technology adoption frameworks are relevant here.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and subsequently extended to financial services contexts (Lai, 2017), posits that user adoption of technology is determined by perceived usefulness and perceived ease of use. Applied to digital KUR, TAM suggests that micro-entrepreneurs who perceive digital lending platforms as useful and user-friendly may be more receptive to credit offers, potentially overriding traditional barriers such as income concerns.

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003) and extended to consumer contexts as UTAUT2 (Venkatesh et al., 2012), incorporates additional constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions. In the digital microfinance context, UTAUT2 provides a comprehensive framework for understanding why some micro-entrepreneurs embrace digital KUR while others remain reliant on traditional channels—a dynamic that may moderate the relationship between economic perceptions and credit decisions.

These frameworks are not tested empirically in the present study but serve as theoretical lenses for interpreting the findings and generating implications for future research.

2.8 Hypotheses Development

Based on the preceding literature review, the following hypotheses are proposed:

H1: Income perception has a significant effect on KUR uptake decisions among micro-entrepreneurs in Kecamatan Palaran.

H2: Interest rate perception has a significant positive effect on KUR uptake decisions among micro-entrepreneurs in Kecamatan Palaran.

H3: Income perception and interest rate perception simultaneously have a significant effect on KUR uptake decisions among micro-entrepreneurs in Kecamatan Palaran.

2.9 Conceptual Framework

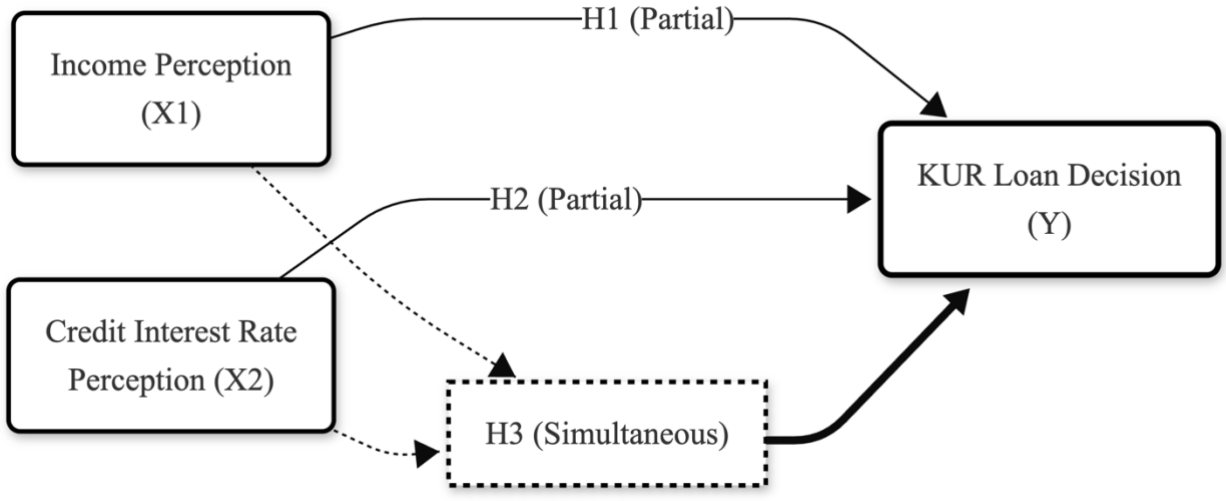

Figure 1. Conceptual Framework

The conceptual framework positions income perception (X_1) and interest rate perception (X_2) as independent variables influencing KUR uptake decisions (Y). The broader digital financial inclusion environment—encompassing digital KUR platforms, AI-driven credit assessment, mobile banking infrastructure, and information transparency mechanisms—is conceptualized as a contextual moderating layer that shapes the informational and behavioral conditions under which these perceptual variables operate. This framework acknowledges that while the digital context is not directly measured in this study, it constitutes the environmental reality within which contemporary microcredit decisions are made.

3. METHODS

3.1 Research Design

This study employs a quantitative research design with a cross-sectional survey approach. Quantitative methods are appropriate for this investigation as they enable the systematic collection of numerical data and the application of statistical analysis to test predetermined hypotheses regarding the relationships between independent and dependent variables (Creswell & Creswell, 2018; Sugiyono, 2019). The cross-sectional design captures the perceptual and behavioral characteristics of micro-entrepreneurs at a specific point in time, providing a snapshot of the determinants of KUR uptake decisions during the ongoing period of financial digitalization in Indonesia.

The study draws on both primary and secondary data sources. Primary data were collected directly from micro-enterprise owners through a structured questionnaire, while secondary data—including the number of registered micro-enterprise licenses and KUR distribution statistics—were obtained from the Kecamatan Palaran sub-district office and publicly available government databases.

3.2 Research Setting and Context

The study was conducted in Kecamatan Palaran, a sub-district within the city of Samarinda, the capital of East Kalimantan Province, Indonesia. Kecamatan Palaran was selected as the research site for several reasons. First, it is a developing urban district with a substantial and growing micro-enterprise population, as evidenced by the steady increase in micro-business license registrations throughout 2024. Second, the area represents the intersection of traditional economic activity and emerging digital financial infrastructure, making it a relevant context for studying the interplay between conventional credit determinants and the evolving digital environment. Third, Kecamatan Palaran remains underrepresented in the existing literature on MSME finance, which has predominantly focused on Indonesia's major metropolitan centers, thereby offering an opportunity to diversify the geographic evidence base.

3.3 Population and Sampling

The target population comprised all registered micro-enterprise owners operating in Kecamatan Palaran as of the data collection period in 2024. A sample of **50 respondents** was drawn using **purposive sampling**, a non-probability sampling technique in which participants are selected based on predefined criteria relevant to the research objectives (Nazir, 2017; Sugiyono, 2019).

The inclusion criteria for respondent selection were: (1) the individual must be a registered owner or operator of a micro-enterprise in Kecamatan Palaran; (2) the enterprise

must meet the legal definition of a micro-enterprise under Indonesian Law No. 20 of 2008, specifically having net assets of no more than IDR 50 million (excluding land and buildings) or annual revenue of no more than IDR 300 million; and (3) the respondent must have awareness of or prior experience with the KUR program.

Justification for sample size. A sample of 50 respondents is consistent with established guidelines for exploratory quantitative research in localized geographic contexts. Sugiyono (2010) recommends a minimum sample size of 30 for statistical validity in survey-based research, with larger samples preferred when feasible. Hair et al. (2019) similarly note that for regression analyses with two to five independent variables, a minimum sample size of 50 is generally adequate to detect medium-to-large effect sizes. Furthermore, studies investigating microcredit behavior in specific sub-district or village-level populations commonly employ sample sizes in the range of 30–100, given the inherent constraints of a geographically bounded target population (Banerjee et al., 2015; Nayak & Mahapatra, 2021). The present sample size thus represents a reasonable balance between statistical requirements and the practical realities of conducting field research within a single sub-district.

3.4 Data Collection Instrument

Data were collected using a structured, self-administered questionnaire comprising 12 items distributed across three variables. All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), a format widely used in perception-based research in financial services (Ghozali, 2016).

Prior to full deployment, the questionnaire was pilot-tested with 30 respondents (not included in the final sample) to assess the validity and reliability of the instrument. This pilot testing phase serves as a safeguard against measurement error and ensures that the items adequately capture the intended constructs before the main data collection commences.

3.5 Operationalization of Variables

The study examines two independent variables and one dependent variable, operationalized as follows:

Table 1. Variable Operationalization

Variable	Role	Indicators	Items	Source
Income Perception (X_1)	Independent	(1) Perceived income adequacy for business needs; (2) Perceived effect of income growth on credit interest; (3) Perceived income stability and confidence in taking KUR; (4) Perceived ease of credit application based on income level	4 items	Suroto (2000); Hutapea & Dewi (2021); Ilza (2023)
Interest Rate Perception (X_2)	Independent	(1) Perceived fairness of bank interest rate setting; (2) Perceived impact of high interest rates on reluctance to borrow; (3) Preference for banks with lower interest rates; (4) Perceived influence	5 items	Kasmir (2010); Warjiyo & Solikin (2003); Sinungan (2008)

		of interest rate information on credit decisions; (5) Willingness to take KUR despite slightly higher rates if benefits are large		
KUR Uptake Decision (Y)	Dependent	(1) Perceived benefit of KUR for business development; (2) Consideration of KUR terms and conditions before application; (3) Confidence in decision to take KUR	3 items	Balqiah & Setyowardhani (2014); Regulation of Coordinating Minister for Economic Affairs No. 8/2015

3.6 Data Analysis Techniques

Data analysis was conducted in two stages, employing a **dual analytical approach** that combines SPSS version 25.0 and SmartPLS 3.0. This methodological triangulation strategy leverages the complementary strengths of both software platforms to enhance the robustness of the findings (Ghozali, 2016; Hair et al., 2019).

Stage 1: Measurement model assessment (SmartPLS 3.0). Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to evaluate the measurement model, specifically the convergent validity and discriminant validity of the constructs. Convergent validity was assessed using two criteria: (a) outer loading values, with a threshold of ≥ 0.70 as the primary standard and ≥ 0.50 as acceptable for exploratory research (Abdullah, 2015; Hair et al., 2019); and (b) Average Variance Extracted (AVE), with a threshold of > 0.50 indicating that the construct explains more than half of the variance of its indicators. Construct reliability was evaluated using Cronbach's Alpha, with values exceeding 0.60 considered acceptable (Ghozali, 2016).

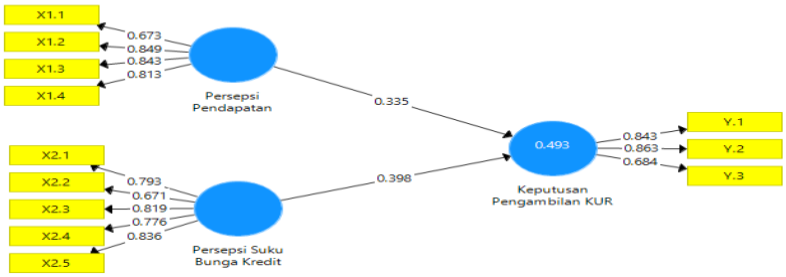

Figure 2. Smart-PLS Outer Loading

Stage 2: Hypothesis testing (SPSS 25.0). Multiple linear regression analysis was employed to test the hypothesized relationships between the independent variables (income perception and interest rate perception) and the dependent variable (KUR uptake decision). The regression model is specified as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

Where:

- Y = KUR uptake decision
- X_1 = Income perception
- X_2 = Interest rate perception
- β_0 = Constant
- β_1, β_2 = Regression coefficients

- ε = Error term

Three statistical tests were conducted:

1. **F-test (simultaneous significance test):** To determine whether the independent variables jointly exert a statistically significant effect on the dependent variable. The decision criterion is based on the comparison of the F-statistic with the critical F-table value and the significance level (α = 0.05).
2. **t-test (partial significance test):** To assess the individual contribution of each independent variable to the dependent variable. A variable is considered to have a statistically significant effect if the p-value is less than 0.05 and the absolute t-statistic exceeds the critical t-table value.
3. **Coefficient of determination (R^2):** To evaluate the proportion of variance in the dependent variable that is explained by the independent variables jointly. The R^2 value indicates the explanatory power of the regression model, with the complement ($1 - R^2$) representing the proportion of variance attributable to factors not included in the model.

Rationale for dual analysis. The use of both PLS-SEM and OLS regression represents a deliberate methodological strategy. SmartPLS 3.0 was employed for its strength in evaluating measurement models with relatively small sample sizes, as PLS-SEM does not require assumptions of multivariate normality and is well-suited to exploratory research contexts (Hair et al., 2019). SPSS 25.0 was subsequently used for hypothesis testing via multiple linear regression, which provides straightforward coefficient estimates, significance tests, and model fit statistics that facilitate clear interpretation and comparability with prior studies in the microfinance literature. This dual approach enhances methodological rigor by ensuring that the measurement properties of the constructs are validated before the structural relationships are tested.

4. RESULTS

4.1 Validity Testing

The validity of the research instrument was assessed through two complementary approaches: bivariate correlation analysis (SPSS 25.0) and outer loading evaluation (SmartPLS 3.0).

Bivariate correlation analysis. The questionnaire was initially pilot-tested with 30 respondents to determine item validity using the Pearson product-moment correlation coefficient. An item was considered valid if its computed r-value (r_calculated) exceeded the critical r-table value at the 5% significance level. For a sample of 30, the critical r-table value is 0.361.

Table 2. Validity Test Results (Bivariate Correlation)

Variable	Item No.	r-table (5%)	r-calculated	Sig.	Status
Income Perception (X1)	1	0.361	0.885	0.000	Valid
Income Perception (X1)	2	0.361	0.657	0.000	Valid
Income Perception (X1)	3	0.361	0.627	0.000	Valid
Income Perception (X1)	4	0.361	0.828	0.000	Valid
Interest Rate Perception (X2)	5	0.361	0.902	0.000	Valid
Interest Rate Perception (X2)	6	0.361	0.608	0.000	Valid
Interest Rate Perception (X2)	7	0.361	0.729	0.000	Valid
Interest Rate Perception (X2)	8	0.361	0.711	0.000	Valid
Interest Rate Perception (X2)	9	0.361	0.760	0.000	Valid
KUR Uptake Decision (Y)	10	0.361	0.744	0.000	Valid

KUR Uptake Decision (Y)	11	0.361	0.887	0.000	Valid
KUR Uptake Decision (Y)	12	0.361	0.680	0.000	Valid

Source: SPSS 25.0 output, processed in 2025.

As shown in Table 2, all 12 questionnaire items produced r-calculated values exceeding the critical r-table value of 0.361, with all significance values at 0.000 ($p < 0.01$). Accordingly, all items were confirmed as valid measures of their respective constructs.

Outer loading analysis (PLS-SEM). Convergent validity was further evaluated using outer loading values generated by SmartPLS 3.0. The primary threshold for acceptable outer loadings is 0.70 (Hair et al., 2019). The majority of items met this criterion. Three items produced outer loading values of approximately 0.60; however, following Abdullah (2015), outer loadings between 0.50 and 0.60 are considered acceptable in exploratory research, provided that the Average Variance Extracted (AVE) for the construct exceeds 0.50.

Average Variance Extracted (AVE). To further confirm convergent validity, the AVE for each construct was examined. An AVE value greater than 0.50 indicates that the construct accounts for more than half of the variance of its indicators, thereby satisfying the convergent validity requirement (Fornell & Larcker, 1981; Hair et al., 2019).

Table 3. Construct Validity — Cronbach's Alpha and AVE (SmartPLS 3.0)

Construct	Cronbach's Alpha	AVE
KUR Uptake Decision (Y)	0.719	0.641
Income Perception (X1)	0.806	0.636
Interest Rate Perception (X2)	0.839	0.610

Source: SmartPLS 3.0 output, processed in 2025.

Table 3 confirms that all three constructs achieved AVE values above the 0.50 threshold: income perception (AVE = 0.636), interest rate perception (AVE = 0.610), and KUR uptake decision (AVE = 0.641). These results, in conjunction with the outer loading analysis, establish that the measurement model demonstrates adequate convergent validity.

4.2 Reliability Testing

Construct reliability was assessed using Cronbach's Alpha coefficients computed via SPSS 25.0. A construct is considered reliable if its Cronbach's Alpha value exceeds 0.60 (Ghozali, 2016).

Table 4. Reliability Test Results

Variable	Cronbach's Alpha	Threshold (α)	Status
Income Perception (X1)	0.812	0.60	Reliable
Interest Rate Perception (X2)	0.832	0.60	Reliable
KUR Uptake Decision (Y)	0.787	0.60	Reliable

Source: SPSS 25.0 output, processed in 2025.

As presented in Table 4, all variables produced Cronbach's Alpha values well above the 0.60 threshold: income perception ($\alpha = 0.812$), interest rate perception ($\alpha = 0.832$), and KUR uptake decision ($\alpha = 0.787$). The overall Cronbach's Alpha across all instrument items was 0.929, indicating excellent internal consistency. These results confirm that the measurement instrument is reliable and suitable for hypothesis testing.

4.3 Simultaneous Significance Test (F-test)

The F-test was conducted to determine whether income perception (X1) and interest rate perception (X2) jointly exert a statistically significant effect on KUR uptake decisions (Y). The decision criteria are: reject H_0 if the computed F-statistic exceeds the critical F-table value and the significance level is below 0.05.

Table 5. F-test Results

F-calculated	F-table	Sig.	α
22.621	3.20	0.000	0.05

Source: SPSS 25.0 output, processed in 2025.

The results presented in Table 5 indicate that the computed F-statistic (F = 22.621) substantially exceeds the critical F-table value (F-table = 3.20), with a significance value of 0.000 ($p < 0.05$). Consequently, the null hypothesis (H_{o3}) is rejected and the alternative hypothesis (H_3) is accepted, confirming that **income perception and interest rate perception simultaneously exert a statistically significant effect on KUR uptake decisions** among micro-entrepreneurs in Kecamatan Palaran.

4.4 Partial Significance Tests (t-test) and Regression Equation

The t-test was employed to assess the individual (partial) effect of each independent variable on the dependent variable. An independent variable is considered to have a statistically significant partial effect if its significance value is less than 0.05 and its absolute t-statistic exceeds the critical t-table value (t-table = 2.011 for df = n − k − 1 = 47 at α = 0.05).

Table 6. Multiple Linear Regression Results (t-test)

Variable	Coefficient (B)	t-calculated	t-table	Sig.	α
Constant	5.084	—	—	—	—
Income Perception (X1)	0.214	1.839	2.011	0.072	0.05
Interest Rate Perception (X2)	0.201	2.054	2.011	0.046	0.05

Source: SPSS 25.0 output, processed in 2025.

The estimated multiple linear regression equation is:

$$\mathbf{Y = 5.084 + 0.214X_1 + 0.201X_2 + \varepsilon}$$

The results for each variable are interpreted as follows:

H1: Income Perception → KUR Uptake Decision. Income perception (X1) does **not** exert a statistically significant partial effect on KUR uptake decisions. The significance value of 0.072 exceeds the critical threshold of 0.05 ($p = 0.072 > 0.05$), and the computed t-statistic (t = 1.839) falls below the critical t-table value (t-table = 2.011). Accordingly, H_1 is **not supported** (H_{o1} is retained). The regression coefficient of 0.214 indicates a positive directional relationship; however, this effect does not reach conventional levels of statistical significance.

H2: Interest Rate Perception → KUR Uptake Decision. Interest rate perception (X2) exerts a **statistically significant positive** partial effect on KUR uptake decisions. The significance value of 0.046 is below the critical threshold of 0.05 ($p = 0.046 < 0.05$), and the computed t-statistic (t = 2.054) exceeds the critical t-table value (t-table = 2.011). Accordingly, H_2 is **supported** (H_{o2} is rejected). The regression coefficient of 0.201 indicates that a one-unit increase in interest rate perception is associated with a 0.201-unit increase in KUR uptake decision scores, holding income perception constant.

4.5 Coefficient of Determination (R^2)

The coefficient of determination (R^2) was computed to assess the explanatory power of the regression model. The analysis yielded an **R^2 value of 0.499**, indicating that approximately **49.9% of the variance** in KUR uptake decisions among micro-entrepreneurs in Kecamatan Palaran is explained by the combined effect of income perception and interest rate perception. The remaining **50.1%** is attributable to other factors not included in the model.

Table 7. Summary of Hypothesis Testing Results

Hypothesis	Path	Coefficient	t-stat	Sig.	Result

H1	Income Perception → KUR Uptake	0.214	1.839	0.072	Not Supported
H2	Interest Rate Perception → KUR Uptake	0.201	2.054	0.046	Supported
H3	Simultaneous (X1 + X2) → KUR Uptake	—	F = 22.621	0.000	Supported

5. DISCUSSION

This study set out to examine how income perception and interest rate perception shape KUR uptake decisions among micro-entrepreneurs in Palaran, an emerging urban district in East Kalimantan. The empirical results indicate that income perception does not have a statistically significant partial effect on KUR uptake decisions, whereas interest rate perception exerts a significant positive influence. In combination, both variables significantly explain nearly half of the variance in KUR uptake decisions, suggesting that traditional economic perceptions still matter, but in asymmetric ways, within the digitalizing microfinance environment.

The non-significant effect of income perception challenges the conventional view that perceived income adequacy is a universal driver of borrowing behavior in microcredit markets. In classical microfinance settings, higher perceived or actual income is often associated with greater confidence to assume debt obligations and a higher likelihood of applying for credit. However, the finding in this study suggests that, in the context of KUR in Palaran, micro-entrepreneurs' decisions to take credit are not primarily constrained by their own assessment of income sufficiency. One plausible explanation is that the availability of relatively small loan sizes, flexible repayment structures, and government guarantees under the KUR scheme reduces the perceived risk associated with limited or fluctuating income, thereby weakening the role of income perception as a salient decision factor.

The digitalization of KUR distribution may further contribute to this pattern by decoupling income perception from perceived credit accessibility. As digital application channels and automated screening processes become more prevalent, borrowers may view eligibility as being determined more by formal criteria embedded in digital systems than by their subjective sense of income adequacy. In such an environment, micro-entrepreneurs who previously felt excluded from formal credit due to low or unstable income may now perceive KUR as more accessible, regardless of their income self-assessment. This interpretation is consistent with the broader literature suggesting that digital financial services and alternative credit scoring can relax traditional income-based barriers to credit for micro and small enterprises.

In contrast, the significant positive effect of interest rate perception on KUR uptake decisions underscores the enduring importance of borrowing costs in micro-entrepreneurs' credit behavior. Respondents who perceive KUR interest rates as fair and affordable are more likely to decide in favor of taking the loan, confirming the central role of perceived price in microcredit decision-making. This aligns with prior empirical evidence that highlights interest rates as a key determinant of loan demand, particularly in environments where small differences in borrowing costs can substantially affect profit margins and cash-flow management for micro-enterprises. For KUR, the government-subsidized rate of around 6–7 percent appears to be viewed as sufficiently attractive to motivate uptake among micro-entrepreneurs who recognize its relative advantage over commercial lending alternatives.

The digital context likely amplifies the salience of interest rate perception by enhancing information transparency. Through mobile banking applications and online

portals, micro-entrepreneurs can more easily compare interest rates, simulate repayment schedules, and access clear information about the total cost of borrowing. These features may heighten awareness of the financial benefits associated with subsidized KUR interest rates and strengthen the influence of interest rate perceptions on credit decisions. In other words, while digital channels may weaken the perceived constraint of income, they simultaneously sharpen the perceived importance of interest rate advantages.

Taken together, the joint significance of income and interest rate perceptions in explaining KUR uptake decisions suggests that micro-entrepreneurs evaluate government-subsidized credit through a combined lens of affordability and perceived repayment capacity, albeit with differing weights. The results indicate that interest rate perception functions as the more decisive factor, whereas income perception plays a secondary or context-dependent role. This asymmetry has important implications for both policy and practice. For policymakers, it highlights the need to maintain competitive subsidized rates and to communicate these advantages clearly through digital and non-digital channels. For banks and fintech partners distributing KUR, the findings point to the strategic value of transparent interest rate display, interactive loan simulators, and easily understandable repayment information in their digital interfaces.

At the same time, the findings invite further research into the unobserved factors that account for the remaining variance in KUR uptake decisions. Variables such as digital financial literacy, trust in digital platforms, perceived ease of use, social influence, and prior credit experience may interact with income and interest rate perceptions in shaping borrowing behavior. Future studies that explicitly incorporate these digital and behavioral constructs—potentially drawing on frameworks such as TAM or UTAUT—would provide a more comprehensive understanding of how traditional economic perceptions operate within Indonesia's evolving digital microfinance ecosystem.

6. IMPLICATIONS

6.1 Theoretical Implications

This study generates several contributions to the academic literature on microfinance, financial inclusion, and digital lending in emerging economies.

First, the finding that income perception does not significantly predict KUR uptake decisions challenges the conventional assumption that perceived income is a universal determinant of microcredit behavior. While income remains a well-established predictor in traditional lending contexts (Hutapea & Dewi, 2021; Ilza, 2023), the present result suggests that this relationship may weaken as financial services become increasingly digitalized. This contributes to an emerging body of literature arguing that digital financial infrastructure alters the behavioral calculus of borrowing by reducing the informational and procedural barriers that previously made income adequacy a central concern for prospective borrowers (Suri & Jack, 2016; Ghosh & Gonzalez del Mazo, 2023). Future theoretical models of microcredit decision-making should therefore account for the moderating role of the digital environment in shaping the salience of traditional economic perceptions.

Second, the significant positive effect of interest rate perception reinforces the applicability of classical Keynesian investment theory and information asymmetry frameworks (Stiglitz & Weiss, 1981) to contemporary digital microfinance. Importantly, it extends these theories by suggesting that digital platforms do not merely transmit interest rate information but actively amplify its influence on borrower behavior through transparency mechanisms and digital nudging (Mirsch et al., 2017). This finding contributes to the theoretical integration of behavioral economics with digital finance by demonstrating

that interface-mediated information framing can strengthen the causal link between economic perceptions and financial decisions.

Third, the substantial unexplained variance (50.1%) in the model provides a clear empirical basis for expanding theoretical frameworks of microcredit decision-making to incorporate digital constructs. Specifically, the Technology Acceptance Model (Davis, 1989), the UTAUT2 framework (Venkatesh et al., 2012), and digital financial literacy theories (Lusardi & Mitchell, 2014; Setiawan et al., 2021) emerge as promising complementary lenses that could enhance the explanatory power of future models in this domain.

6.2 Practical Implications

The findings offer actionable insights for commercial banks, fintech companies, and microfinance institutions involved in KUR distribution.

For banking institutions and digital platform designers. The significance of interest rate perception, combined with the non-significance of income perception, suggests that KUR marketing and digital platform design should prioritize the transparent and prominent display of interest rate information. Practical recommendations include: developing interactive loan calculators that allow prospective borrowers to simulate monthly installments under various scenarios; implementing comparative rate dashboards that juxtapose KUR rates with commercial alternatives; and deploying AI-powered chatbot systems that can provide personalized interest rate explanations and answer borrower queries in real time. These features leverage the demonstrated behavioral importance of interest rate perception while utilizing digital tools to enhance borrower engagement.

For micro-entrepreneurs. The results suggest that micro-enterprise owners benefit from focusing their credit evaluation on the cost structure of available loans rather than solely on their income capacity. Financial education programs targeting micro-entrepreneurs should emphasize skills in comparing interest rates across products, understanding the total cost of borrowing, and utilizing digital tools—such as mobile banking applications and online loan simulators—to make informed credit decisions.

6.3 Policy Implications

The findings carry direct implications for Indonesian government agencies and policymakers responsible for KUR program design and financial inclusion strategy.

Digital KUR distribution policy. The significance of interest rate perception in driving KUR uptake validates the government's ongoing efforts to maintain the KUR subsidized interest rate at competitive levels (currently 6–7% per annum). However, the results suggest that the policy emphasis should extend beyond rate-setting to encompass **how** rate information is communicated to prospective borrowers through digital channels. Policymakers should mandate standardized transparency requirements for digital KUR platforms, ensuring that interest rate information is presented in clear, comparable, and accessible formats across all distribution channels.

AI integration in KUR distribution. The unexplained variance of 50.1% in the present model, combined with the growing availability of behavioral and transactional data from digital platforms, presents an opportunity for the strategic integration of AI into KUR distribution systems. Figure 2 presents a conceptual framework for an AI-enhanced KUR distribution model.

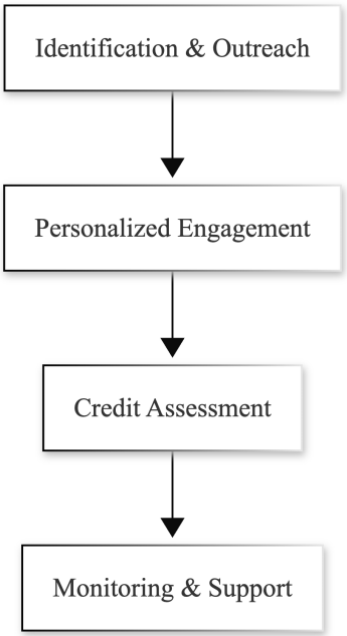

Figure 3. Proposed KUR Distribution Framework

This framework proposes a four-stage AI-enhanced KUR distribution system that incorporates the empirical insights of the present study. Stage 1 employs predictive analytics to proactively identify eligible micro-entrepreneurs, moving beyond passive application-based models. Stage 2 leverages the finding that interest rate perception is a significant driver of KUR uptake by designing AI-powered engagement tools that enhance borrowers' understanding and perception of interest rate affordability. Stage 3 integrates AI-driven credit scoring that supplements (rather than replaces) traditional income assessment—acknowledging the present study's finding that income perception alone is an insufficient predictor of credit behavior. Stage 4 introduces post-disbursement monitoring capabilities that create a continuous feedback loop for system improvement.

Digital literacy and inclusion policy. The identification of digital literacy, platform usability, and digital trust as plausible candidate variables for the unexplained variance (Section 5.3) suggests that financial inclusion policies should invest not only in digital infrastructure development but also in digital literacy programs targeted at micro-entrepreneurs. The Indonesian government's National Strategy for Financial Literacy and Inclusion (SNLKI) should explicitly integrate digital financial skills into its curriculum, with particular attention to underserved areas such as Kecamatan Palaran where the digital transformation of financial services is still in its early stages.

7. CONCLUSION

This study examined the influence of income perception and interest rate perception on Kredit Usaha Rakyat (KUR) uptake decisions among micro-entrepreneurs in Kecamatan Palaran, Samarinda, East Kalimantan, within the broader context of Indonesia's ongoing digitalization of microfinance services.

The empirical findings reveal a nuanced pattern. Income perception does not exert a statistically significant effect on KUR uptake decisions ($p = 0.072$), suggesting that micro-entrepreneurs in this context do not regard their perceived income level as a decisive factor when evaluating microcredit opportunities. In contrast, interest rate perception exerts a statistically significant positive effect ($p = 0.046$), confirming that the perceived affordability

and fairness of borrowing costs remain central to microcredit decision-making. When considered jointly, both variables significantly predict KUR uptake decisions (F = 22.621, p = 0.000), explaining 49.9% of the variance in the dependent variable.

These findings, interpreted within the evolving landscape of digital financial services, suggest that the digitalization of microfinance may be reshaping the relative importance of traditional economic determinants of credit behavior. The diminishing role of income perception may reflect the democratizing effect of digital platforms, which lower access barriers and reduce the salience of income-based eligibility concerns. Conversely, the persistent and amplified role of interest rate perception may be attributable to the enhanced information transparency afforded by digital interfaces, which make borrowing costs more visible, comparable, and actionable for micro-entrepreneurs.

The study contributes to the literature by bridging classical microfinance theory with the emerging discourse on digital financial inclusion and AI-driven credit assessment, offering empirical evidence from an underrepresented geographic context in Indonesia. The proposed AI-Enhanced KUR Distribution Framework provides a conceptual roadmap for integrating the study's behavioral insights into technology-driven policy solutions that can improve the targeting, transparency, and effectiveness of government-subsidized microcredit programs in emerging economies.

As Indonesia and comparable developing nations continue to digitalize their microfinance infrastructure, understanding the interplay between borrowers' subjective economic perceptions and the digital environments in which credit decisions are made will become increasingly essential for policymakers, financial institutions, and technology developers committed to advancing financial inclusion.

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