Explainability of AI Credit Decisions and BNPL Continuance: The Moderating Role of Financial Literacy

V.K.P. Yasithanjanee, J.M.D. Rashodya, S. Venukanan & S. Rajakarunanayake
Department of Industrial Management, Faculty of Business, University of Moratuwa, Moratuwa, Western Province, Sri Lanka

ABSTRACT: Artificial Intelligence (AI) is increasingly used in Buy Now, Pay Later (BNPL) services to support automated credit decisions. This study examines the association between perceived explainability of AI credit decisions and consumers' continuance intention to use BNPL services and assesses the moderating role of financial literacy in Sri Lanka. A quantitative cross-sectional survey of 404 BNPL users was analysed using IBM SPSS Statistics and Hayes' PROCESS Macro. Perceived explainability was positively and significantly associated with continuance intention. Financial literacy showed a positive direct association with continuance intention, but its interaction with perceived explainability was not statistically significant. Thus, financial literacy did not moderate the focal relationship. The findings extend explainable-AI research to post-adoption BNPL use and highlight the relevance of understandable AI-supported credit decisions.

Keywords: Explainable AI, BNPL, perceived explainability, continuance intention, financial literacy

1 INTRODUCTION

Artificial Intelligence (AI) has found its way into various aspects of financial services, including credit assessment, fraud detection, risk management, and personalized financial services [1], [2]. Buy Now Pay Later (BNPL) is one such digital financial innovation that allows consumers to buy products right away with the ability to pay for them in installments. The automated credit assessment and fast eligibility checks offered by AI can be beneficial for providers, helping expedite the lending process and improve its ease [3], [4] another hallmark of BNPL services. With the increasing popularity of BNPL, the focus is now shifting from adoption to understanding the reasons behind the continued use of these services by consumers.

This is particularly important because automatic credit decisions may seem to be "black box" decisions. Consumers may get an approval, rejection, or a credit-related outcome without being aware of the factors or the reason for the result [1], [5]. To overcome this, Explainable Artificial Intelligence (XAI) aims to make the decisions made by AI more understandable and interpretable to humans [1], [6]. Perceived explainability, on the consumer side, is the degree of transparency and/or meaning of the reasoning behind an AI decision that users think is understandable [6], [7]. Previous research has linked users to positive impressions of AI systems when they find their explanations to be understandable, such as trust, acceptance, perceived usefulness, and intentions to use AI in decision-making [7]. But relatively little has been paid attention to regarding post-adoption continuance intention, especially in credit decision making on AI-assisted BNPL.

Users' reactions to credit decision explanations could also be influenced by financial literacy. Financially knowledgeable con-

sumers might be more capable of understanding the repayment demands, loan terms and other factors that relate to the use of BNPL [8]. Thus, perceived explainability could be a boundary condition of the relationship between these two. However, this is an under-researched aspect in the Sri Lankan BNPL landscape, where digital financial services and instalment payments have grown [9]. The present study hence explores the relationship between perceived explainability of AI credit decisions to continuance intention to use the BNPL services and the impact of financial literacy on this relationship. Theoretically, ECM is adopted to interpret post-adoption behaviour, but not in its original form as it is not tested in this study. The study extends explainable AI research to the continued use of BNPL and looks at financial literacy as a potential moderator of consumers' reactions to the explainable credit decisions.

Based on these gaps, the study addresses two questions: whether perceived explainability of AI credit decisions is associated with continuance intention to use BNPL services, and whether financial literacy moderates this relationship. Accordingly, the study aims to examine this association and assess the moderating role of financial literacy. Empirically, the study provides evidence from Sri Lankan BNPL users, while practically, it offers insights for BNPL providers and financial service developers in designing clearer and more understandable AI-supported credit decision processes.

2 LITERATURE REVIEW

2.1 *Theoretical foundation*

The Expectation-Confirmation Model (ECM) [10] The major behavioural lens for this study is the Expectation-Confirmation Model (ECM) [10]. According to ECM, information-system continuance is a post-adoption process that occurs after the initial use of a system in which the information system users assess their experiences with the system. For the original model, factors of central importance to the continuance intention are confirmation, perceived usefulness, and satisfaction [10]. Not all these constructs are measured or tested in the present research. Rather, ECM is seen as being part of a larger theory that post-adoption studies of a digital service are relevant to users' intentions to keep using the service. For BNPL, consumers repeatedly face decisions around eligibility and credit; thus, their perception of how intuitive and understandable the decisions are may be integral to the entire BNPL post-adoption experience.

The study also adopts the Fairness, Accountability, Transparency, and Explainability (FATE) lens to gain an understanding of the conceptual significance of explainability in responsible AI. In the context of FATE, research has focused on enabling users to understand the foundations of consequential automated decisions, and to make explainability a part of more accountable and trustworthy AI systems [1], [11]. In financial services, this concern becomes especially important with algorithmic credit decisions impacting payment and borrowing opportunities. The two perspectives are therefore complementary: FATE argues that explainability is important in AI-assisted decision-making, while ECM offers a lens to reflect on the explanation's influence on the favorability of the decisions made, which might be linked to continued service use. This positioning refrains from using FATE as a behavioural continuance theory or from empirically testing the whole ECM in this study.

2.2 *Explainable AI and perceived explainability*

The need for XAI came in part due to the lack of transparency in complex AI and machine-learning systems, which are sometimes referred to as ‘black boxes' [1] as they may lack a readily available explanation of the underlying process behind their predictions or classifications. This opacity is important in contexts like finance, where users might want to know the rationale behind a credit-related decision. The concept of XAI can be broadly defined as the various approaches that seek to make automated decision-making processes more interpretable, and the concept of perceived explainability specifically considers the user's subjective perception of the understandability and meaningfulness of the explanation [6], [7]. An available explanation is not always a good explanation from the consumer's point of view.

Previous studies have shown that explanations can influence users' perceptions of AI systems. Previous research and perception studies show that the ability to provide

explanations boosts trust, acceptance, perceived usefulness, and the tendency to trust an AI-backed decision [6]. The findings are applicable to BNPL, as consumers might be subjected to automated eligibility checks or credit checks multiple times in instalment payments. If the user can understand the key reason given around these decisions, they can make a more favorable assessment of the service. The present study does not test a specific technique of XAI or technical transparency of a particular algorithm, but rather investigates consumer perception of their understanding of the AI-based decision on lending. Perceived explainability is thus considered to be a construct on the user level, which can be evaluated in terms of post-adoption behavior.

2.3 *Perceived explainability and continuance intention (H1)*

Perceived explainability might be important for continued use, as credit decisions that are understood by customers will lower uncertainty and allow consumers to evaluate the automated process. Earlier research has found a link between understandability of explanations of AI decisions and positive attitude toward AI, as well as acceptance and use of AI-based tools [6], [7]. In BNPL services, customers can experience multiple instances of automated credit decisions as they request installment payment. Similarly to the post-adoption principles of ECM, positive evaluation of the process could be connected with continued usage intentions [10]. Therefore, when the customer perceives AI credit decisions as understandable and meaningful, he/she would report greater continuance intention.

H1: Perceived explainability of AI credit decisions is positively associated with consumers' continuance intention to use BNPL services.

2.4 *Moderating role of financial literacy (H2)*

Financial literacy is defined as an individual's competence in financial terms and the use of financial information for decision-making [8]. In the case of BNPL services, financially literate customers can be in a better position to appraise their debt requirements, credit terms, and information provided with the help of the automated lending decision. Thus, it is hypothesized that financial literacy acts as a moderator and alters the magnitude of perceived explainability on continuance intention. It is likely that financially literate consumers will extract higher benefits from an understandable explanation, while consumers with lower financial literacy can face difficulties evaluating the financial meaning of the information provided. Existing studies on BNPL services underscore the importance of financial knowledge in using such services responsibly [8]. Therefore, financial literacy is considered a potential boundary condition in the study.

H2: Financial literacy moderates the relationship between perceived explainability of AI credit decisions and continuance intention to use BNPL services.

2.5 *Conceptual framework*

The conceptual framework positions perceived explainability of AI credit decisions as the predictor of continuance intention and financial literacy as the moderator of that relationship.

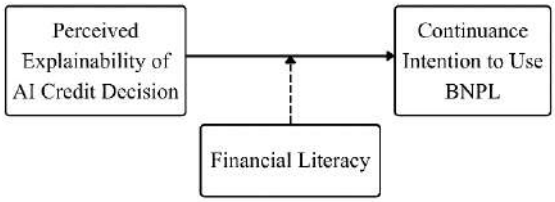


Figure 1. Conceptual framework

3 METHODOLOGY

A quantitative cross-sectional survey design was adopted to explore the relationship between the perceived explainability of AI credit decisions and continuance intention and to test the moderating effect of financial literacy. The target population included Sri Lankan consumers who had previously interacted with e-commerce products that relied on buy now pay later financing (BNPL) like Koko, MintPay, and Payzy. Convenience sampling was used. The questionnaires were collected, with a total of 417 questionnaires, of which 404 questionnaires were valid after data screening and cleaning were performed. The cross-sectional design can be used to study relationships (statistical associations) between the study variables.

The analytical sample included respondents aged 25–34 years (47.2%), 18–24 years (46.8%), 35–44 years (4.7%), and 45–54 years (1.2%). Most respondents were undergraduates (60.1%), followed by the postgraduates (17.3%). The most common BNPL application reported was Koko (80.4%), followed by MintPay (33.9%) and Payzy (8.9%); respondents could report more than one application. In terms of frequency of use, 33.9% had only tried BNPL apps for less than six months, while 30.9% had used the apps for six months to a year, 23.8% for one to two years, and 11.4% for over two years.

The data were gathered using *a* structured, self-administered questionnaire that uses measures adapted from the literature. We measured perceived explainability using five items related to the concept of explanation adapted from [12]and reworded for the context of AI-supported BNPL credit decisions. Continuance intention was measured with three items adapted from [10]. The two of these constructs were measured on seven-point Likert scales where 1 equals Strongly Disagree and 7 equals Strongly Agree. Financial literacy was assessed by three objective knowledge questions which was adapted from [15] and a score was determined based on the number of correct answers. Descriptive, reliability, factor, correlation and regression analyses were conducted using IBM SPSS Statistics, and a moderation analysis was conducted using Hayes' PROCESS Macro.

3.1 *Data analysis and measurement assessment*

Before hypothesis testing, the data were examined for normality, reliability, construct validity, and potential common-method variance. The skewness values ranged from −0.938 to −0.513, while kurtosis values ranged from −0.789 to 1.672, indicating no substantial departure from normality. Internal consistency was assessed using Cronbach's alpha. Perceived Explainability (α = 0.896), Continuance Intention (α = 0.791), and Financial Literacy (α = 0.717) all exceeded the commonly accepted minimum threshold of 0.70, indicating satisfactory reliability.

Construct validity was assessed for the perceptual measures, Perceived Explainability and Continuance Intention, using Exploratory Factor Analysis (EFA). Principal Axis Factoring with Direct Oblimin rotation was applied. The Kaiser–Meyer–Olkin measure was 0.896, while Bartlett's Test of Sphericity was statistically significant, $\chi^2(28) = 1677.139$, $p < 0.001$, confirming the suitability of the data for factor analysis. Two factors were extracted, jointly accounting for 61.19% of the variance. Factor loadings ranged from 0.707 to 0.857 for Perceived Explainability and from 0.673 to 0.817 for Continuance Intention, supporting the expected two-factor structure.

Table 1. Measurement assessment summary

Measure	Items	Cronbach's α
Perceived Explainability	5	.896
Continuance Intention	3	.791
Financial Literacy	3	.717

Common-method variance was also examined because the perceptual measures were collected from the same respondents through a self-administered questionnaire at a single point in time. Harman's single-factor diagnostic showed that a single factor explained 56.76% of the total variance. Since this value exceeds the commonly used 50% diagnostic threshold, common-method variance cannot be completely ruled out. Therefore, the result is not interpreted as evidence that common-method bias is absent; instead, it is acknowledged as a methodological limitation of the study. At the same time, the two-factor EFA showed that Perceived Explainability and Continuance Intention emerged as empirically distinct constructs in the dataset. Accordingly, the findings are interpreted cautiously, and no causal claims are made.

3.2 *Correlation and hypothesis testing*

Pearson correlations showed that Perceived Explainability was positively associated with Continuance Intention ($r = .566$, $p < .001$). Perceived Explainability also had a weak positive association with Financial Literacy ($r = .127$, $p = .010$), while Financial Literacy was positively associated with Continuance Intention ($r = .172$, $p = .001$). These relationships provide preliminary evidence of association among the study variables but do not establish causality.

Table 2. Correlation matrix

Variable	1	2	3
1. Perceived Explainability	1.000		
2. Continuance Intention	.566**	1.000	
3. Financial Literacy	.127**	.172**	1.000

Note: *p < .05; **p < .01.

H1 was tested using simple linear regression. The model was statistically significant, $F(1, 402) = 189.028$, $p < .001$, with $R^2 = .320$ and adjusted $R^2 = .318$. Perceived Explainability was positively associated with Continuance Intention ($B = .354$, $SE = .026$, $\beta = .566$, $t = 13.749$, $p < .001$). Thus, H1 was supported. H2 was tested with PROCESS Model 1. The overall moderation model was significant, $F(3, 400) = 65.809$, $p < .001$, $R^2 = .3305$. Perceived Explainability remained significant ($B = .3461$, $p < .001$), and Financial Literacy showed a positive direct association with Continuance Intention ($B = .2028$, $p = .0145$). However, the PE × FL interaction was not significant ($B = -.0112$, $SE = .0229$, $t = -.4889$, $p = .6252$, 95% CI [-.0562, .0338]), and the interaction added only $\Delta R^2 = .0004$. Therefore, H2 was not supported.

Table 3. Hypothesis-testing summary

Hyp.	Term	B	SE	p	Decision
H1	PE → CUI	.354	.026	<.001	Supported
H2	PE × FL → CUI	−.0112	.0229	.6252	Not supported

H1 model: R^2=.320. H2 moderation model: R^2=.3305; interaction ΔR^2=.0004.

4 FINDINGS AND DISCUSSION

The results support H1 and show that perceived explainability of AI credit decisions is positively associated with continuance intention to use BNPL services. Considering the study sample as a whole, the variance in continuance intention was explained by perceived explainability alone (32.0%), which was considered significant. Those who said the AI-powered credit decisions were more understandable also showed greater plans to use BNPL more. This result aligns with previous studies that demonstrated the positive correlation between explainability and positive user attitudes towards AI, such as acceptance, perceived usefulness, and reliance on automated systems [6], [7]. An understandable explanation can assist users to make sense of repeated interactions with credit and potentially minimize the amount of uncertainty about an automated eligibility decision in a BNPL environment.The result is also coherent with the post-adoption rationale of ECM [10]. ECM suggests that first-time evaluations by users are pertinent to continuance behaviour. In the present study, the relationship we observed suggests that explainability can be regarded as a relevant post-adoption experience attribute of BNPL services using AI.

H2 was not supported. There was no significant moderation effect between perceived explainability and continuance intention (R^2 change was less than 1%), and the interaction term did not significantly contribute to the model. Within the observed sample, the association between explainability and continuance were not significantly different by financial literacy. But the result does not suggest that financial literacy is not important. In the moderation model, financial literacy had a strong positive association with the intention of continuing the BNPL service, supporting the idea that it could have a moderating effect on consumers' attitudes toward BNPL use in general. But the association between perceived explainability and continuance intention remained the same, irrespective of the level of financial knowledge. A possible explanation is that explanations which are understandable for the credit decision made by AI might be relevant for users with varying degrees of financial literacy. The need for explanation to make decisions about continuance intentions may not be significantly different for highly literate consumers and consumers with limited financial knowledge, and clear communication of why a decision was reached may have value for both groups. This should be interpreted with caution since the interaction was not significant. Future studies might explore the possibility of replacing the general financial literacy boundary condition with AI literacy, digital financial literacy, complexity of explanation, or the type of credit outcome.

5 MANAGERIAL IMPLICATIONS

The results have practical implications for BNPL service providers, financial institutions, and developers of AI-based credit decision-making systems. In light of the positive association between perceived explainability and the willingness to continue using the service, providers should clearly communicate the automated credit decision to users. Instead of providing just the credit decision outcome (approved or rejected), the interface should provide an explanation of what are the key criteria used in the decision, its interpretation and, when necessary, information about repayment or eligibility requirements. Explanations should not contain unnecessary jargon and should take into account different levels of consumers' financial literacy. In view of the lack of a moderating effect, understandable explanations should not target solely financially literate users. On the other hand, the positive direct association between financial literacy and the continuance intention indicates that financial education and transparency in explaining instalments is beneficial overall.

6 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

There are some restrictions to be considered. Firstly, the cross-sectional survey design allows for statistical associations to be examined, but not for causal relationships or changes in perceptions over time. To test the effects of different explanation designs and temporal ordering more directly, longitudinal or experimental research could be conducted. Second, convenience sampling and the inclusion of local Sri Lankan BNPL users reduce the ability to generalize to other populations, markets, and digital-credit environments. Samples from different probability samples or cross-country comparisons could be used in future studies.

Third, common-method variance cannot be completely excluded, as the perceptual variables were measured with the same respondents at the same time. Further study might be done to partition measurements temporally, multiple data sources could be used, or statistical controls could be applied more rigorously. Fourth, this study concentrates on perceived explainability, financial literacy, and continuance intention. Some variables like trust, perceived fairness, perceived risk, AI literacy, satisfaction, and perceived usefulness may be incorporated to examine more complex behavioural mechanisms and more comprehensive theoretical models. The reliance on just three objective financial-literacy indicators is another reason to consider other indicators of consumers' financial capability in future research.

7 CONCLUSION

The current research focused on how the perceived explainability of AI credit decisions is linked to consumers' continuance intention to use BNPL services and explored financial literacy as a moderator among Sri Lankan BNPL users. The perceived explainability was significant and positively correlated with continuance intention, and the interaction between perceived explainability and financial literacy was not significant. Financial literacy therefore did not moderate the focal relationship. The study extends existing explainable-AI literature towards post-adoption behaviour and shows the importance of users' understanding of automated credit decisions in the BNPL context. The findings also highlight the need to differentiate between observed associations and causal claims and to differentiate the current results from unmeasured mechanisms like trust. The findings support the notion that perceived explainability is a relevant correlate of BNPL continued use intentions, and provide a foundation for additional studies based on a longitudinal design.

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