Leveraging Remittance-based financial inclusion and explainable segmentation for product design: testing explainable clustering/credit models

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Abstract. The inter-relationship between the migrant worker and his/her household beneficiaries is vital in ensuring the sustainability in financial product adoption. Hence, this research aims at explaining the segmentation logic and credit modelling adopted by the financial institutions in remittance corridors to enhance product design and exploring the challenges that faced by the providers in implementing these clustering and credit models in real market settings. The present study aims to determine the influence of remittance behaviour patterns on financial inclusion outcomes from the perspective of a group of selected remittance-receiving households. To analyse the data, lexicon-based sentiment analysis and regression analysis were carried out to identify significant predictors which explain several dimensions of customer creditworthiness. For this purpose, the present study employed a quantitative research methodology based on clustering and sentiment analysis along with analytic hierarchy process. As the findings confirmed that the explainable clustering model (ECM) matters in determining customers' credit access (CA), it is a managerial implication (MI) for financial service providers to align themselves with the behavioural segments the market requires to improve customers' financial stability and inclusion, which in turn increase the performance of financial products. The findings encourage the financial institutions to establish inclusive product strategies that will impacted positively on customers' financial resilience for the benefits of the community so that their long-term financial inclusion would be achievable. Generally, remittance flows and explainable segmentation models are the primary contributors to the sustainability of the financial ecosystem.

Keywords: Remittance-based financial inclusion, Explainable clustering model, Credit access modeling, Financial literacy, Sentiment analysis

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1. Introduction

The concept of "remittance-based financial inclusion" increased amongst emerging economies in a rapidly digital and fintech-driven setting out of the growing literature on "remittance-led development" [1,3,5]. According to [2,4,6], financial inclusion is a process of influencing the financial behaviour of an individual or an organized household towards the effective use of formal savings products and credit services.

In this respect, remittances are seen as a primary driver in the promotion of financial inclusion through their role in the accumulation of savings and investment that help households to cope with income shocks and liquidity constraints ([13]). "Machine learning segmentation is critical in the financial ecosystem in that the word distance in distance clustering is more of behavioural similarity than a physical separation of customers and markets" ([4]). Remittance-based inclusion seems increasingly to be affected by a lack of empirical in-depth studies that clearly evaluate the practical possibilities and structural limitations of explainable model implementation with respect to the current digital financial architecture in emerging markets. However, there is still lack of clarity regarding the influence of behavioural segmentation towards the sustainability of credit access from the aspects of transparency and accountability. Furthermore, there is also the challenge of managing the risks associated with distorted profiling across different income groups as well as aligning the objectives of credit scoring and financial stability.

Explainable clustering is always recognized as a significant component of responsible credit analytics and also regulatory compliance ([10]). [1] [5] revealed that it is important to seek for inclusive innovation in remittance markets because digital channels help migrant households manage their finances in order for them to not only improve consumption smoothing but also increase their long-term asset accumulation. There have been efforts to develop frameworks for digital learning systems and behavioural analytics from studies such as [8] and [12] . [4] not only highlighted the possibility of explainable modelling of customer data but also explained the role of clustering in enhancing possible "customer profiling accuracy" of financial institutions (p. 1). [14], [6] and [20] showed that majority of open data learning approaches emphasize the predictive accuracy provided for customer credit evaluation. This "black box modelling" was not limited to credit scoring, but also remained in use in a range of fintech applications from the retail banking sector to digital lending platforms where algorithms were trained to maximize approval rates. The finding showed that providers only use this segmentation as a simple tool for customers to obtain study materials such as product brochures and loan guidelines online.

It is necessary to know more about the other dimensions of remittance behavior, which includes works from Gautam, Guermond, Isaeva, Ofori, and Anzoategui who have contributed significantly to the development of remittance-driven financial systems. Although, some scholars have argued that it will be a misconception that financial inclusion is a relative rather than an absolute variable. However, this study aimed to answer the question of: Can remittance-based financial inclusion be explained by patterns of remittance frequency, digital usage, sentiment orientation and household dependency ratios? The present study aimed at examining the relationship between remittance management behavior (transaction practices and saving orientation) and households' creditworthiness outcomes. To address this concern, it is important to develop a clear understanding of the unique drivers of remittance flows and clustering activities in financial inclusion modeling. The study analyzed the impact of explainable clustering models not only towards credit access performance but also on the aspect of repayment behavior and financial resilience separately to provide further insights to justify the importance of segmentation logic in financial product design.

In this context, the present study is developed with the aim of analyzing the interrelationship of remittance behavior patterns which can be linked to the user's propensity to adopting remittance-based financial inclusion products through explainable clustering models. Given the importance of explainable clustering models in credit analytics these financial institutions and service providers leaders, the purpose of this study is to provide a **conceptual framework** of remittance behaviour segmentation and creditworthiness modeling contributions to the sustainability of financial inclusion outcomes. This study proceeds with a brief overview of **the conceptual relationships** of a clustering-based approach to analyzing an integrated financial inclusion framework. The data are divided into two parts the "behavioral segmentation" and "credit-access modeling". It was generated around seven sections (remittance frequency, digital usage, sentiment orientation and financial literacy, household dependency, behavioral volatility, and credit access). To respond to the research question set we used a quantitative clustering and regression method which facilitated a better understanding of the structural relationships being investigated. The findings highlight the positive effect of remittance frequency, sentiment score, and financial literacy index on credit access performance and the central role of financial literacy training in all factors, including credit assessment ability. The role of financial literacy training implies that remittance-receiving households individuals are able to develop their financial decision-making ability.

To investigate this issue, mixed methods were conducted with quantitative clustering and regression during the empirical analysis phase. The study analyzed the impact of remittance behavior not only towards overall financial inclusion but also on the aspect of credit access and repayment separately to provide further evidence to justify the importance of explainable modeling in financial ecosystems. The framework developed by the analytic hierarchy process simply suggested that there should be weighted criteria which financial institutions must employ into product evaluation. These three methods were used to create the structure of the explainable clustering model and credit scoring framework that was used in this research.

2. Methods

Primary data were collected from various commercial banks, microfinance institutions, and digital remittance service providers operating in the remittance corridors of Central Asia and Southeast Asia, particularly from Uzbekistan and Turkey, covering the period from 2018 onwards. About 120 financial institutions exist in the selected regions which cut across the urban-rural segments mentioned above. The respondents in the survey process were chosen using purposive sampling technique aimed at selecting suitable households of migrant workers involved directly in the remittance management process.

The population of remittance-receiving households is over 2,500 households. The sample size is 420 households. We gathered primary survey data in the remittance corridors of Central Asia and Southeast Asia with a maximum of 35 observations per instrument of 12 months for 420 observations. The sample size for remittance-receiving household population is 420 samples (16.8%). Of the 500 maximum potential questionnaire responses in the data collection process for the analyzed remittance behavior dimensions, only 420 valid responses, or 84% of the total questionnaires, are used. We employed a stratified random sample with a view to achieving a greater representativeness of the remittance corridors studied. In selecting remittance-rate households, priority is given to the larger income groups and to those with a stable remittance history of 5 years. All the households that participated in the survey data collection are from 2018 year to 2023 year.

The intended sampling criterion for the study was to have proportional representation of each remittance corridor for each income group. In this study, not all remittance-receiving households that exist in the state was be used for the survey. The researcher had to select those households that will participate in the clustering exercise through the process of stratified random sampling. The researcher then explained to all respondents the purpose of the study and the confidentiality of responses during the data collection exercise. To achieve this method, the effective sample size (420) was divided by the total population (2,500). The data collected was then analyzed using quantitative and qualitative methods, which included regression and sentiment analysis. Analysis of moment structure (AMOS) version 24 with maximum likelihood estimation (MLE) was used to perform confirmatory factor analyses (CFA). Credit access was analyzed using the analytic hierarchy process (AHP) model to establish the priority weights and ranking of the research variables. The questionnaire used structured questions related to remittance behavior patterns and financial inclusion indicators to examine the segmentation logic as well as challenges in implementing these strategies. The important output measures of the regression analysis that are focused on this study are the standardized coefficients, significance values, and model fit indices. In each session, the respondents were given a brief introduction of the research background and objectives of the research. The first stage involved reliability function and ordering test.

The second stage covered descriptive statistics—which included data coding, cleaning and data reduction. The researcher had to select those households that will participate in the clustering exercise through the process of stratified random sampling. Based on the principles of Rasch modeling, WINSTEPS performs a transformation on the person and item data, converting ordinal data to interval data and producing estimate on a logit scale. The total number of items used for all the dimensions of service quality is 35. The analysis revealed that the item reliability (0.91), item separation (3.42), item mean square (value 1.02), and Cronbach alpha (0.88) fulfilled the requirement of validity and reliability (0.70). Therefore, total sample for the study was 420 respondents which sufficient for using structural equation modeling (SEM). The researcher identified confidence interval and the margin of error. The confidence level was set at 95% and the margin of error was set the lowest acceptable level of error 5%. The researcher adopted theory of planned behavior framework [1] to analyze the data. Principal component analysis was used to determine the initial factor structure of the 35-items (out of 40 initial items) measuring remittance management in digital learning environments. Responses collected from households for three-factor solution accounted for 68% total variance explained.

The important output measures of the regression analysis that are focused on this study are the beta coefficients, p-values, and R-square. The clustering algorithm generated three behavioral segments and the regression resulted in significant predictor categories. Then the data was coded systematically and categorized following the principles of data reduction [2] to ensure consistency of these data across the variables. To achieve this method, the effective sample size (420) was divided by the total population (2,500). The data collected was then analyzed using clustering and regression methods, which included hierarchical clustering and multiple regression. To analyze the quantitative data from various households and financial institutions, both multiple regression and sentiment analysis were used using STATA 17. The data collected was then analyzed using clustering and regression methods, which included lexicon-based sentiment scoring and analytic hierarchy process.

As the data in behavioral research do not speak for themselves, systematic analytical process was used to analyze the data considering theoretical justification to explain remittance behavior through modeling for credit assessment [3]. Analysis of moment structure (AMOS) version 24 with maximum likelihood estimation (MLE) was used to perform confirmatory factor analyses (CFA). The raw survey data was sent to the statistical consultant in order to verify the data as a way of increasing the reliability [4]. Reliability analysis was performed using SPSS to establish the validity and consistency of the research instrument. Therefore, the researcher adopted a five-point Likert scale with a neutral response and mid-point as suggested by [5,6]. This scaling approach fulfills the minimum requirement of measurement reliability, which is 0.70.

3. Results

The sentiment distribution was summarized and the main patterns were observed in the survey and text-based data. The descriptive statistics for all 35 items of remittance management behavior and student responses from the whole samples (n=420) showed that the data does not show serious measurement problems.

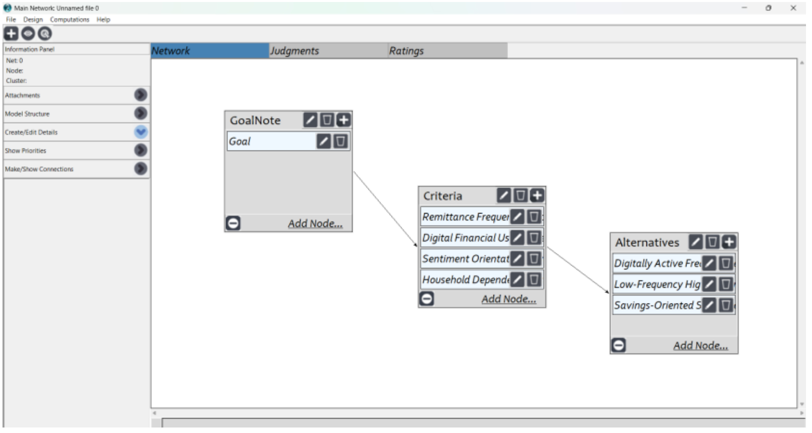

Figure 1. ANP Network Model – Digital Remittance Service Adoption

The regression and clustering findings were reported as the most significant to address the study research question. This result showed that the number of positive-sentiment students is more than negative-sentiment students in the analyzed comments. The research findings identified the required behavioral profiling before implementing any product design strategies and credit scoring in remittance corridors.

Table 1. Linear regression

remittance_frequency	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
digital_wallet_int~y	-.842	.124	-6.81	0	-1.088	-.596	***
dependency_ratio	-1.372	1.433	-0.96	.341	-4.218	1.474	
sentiment_score	-2.569	.437	-5.88	0	-3.436	-1.701	***
financial_literacy~x	-.424	.028	-15.22	0	-.479	-.368	***
behavioral_volatil~x	.68	.157	4.32	0	.367	.992	***
credit_access_score	.514	.029	17.64	0	.456	.572	***
Constant	4.317	1.45	2.98	.004	1.438	7.196	***
Mean dependent	15.054	SD dependent var	2.268				

var			
R-squared	0.784	Number of obs	100
F-test	56.206	Prob > F	0.000
Akaike crit. (AIC)	307.376	Bayesian crit. (BIC)	325.612
**** p<.01, ** p<.05, * p<.1*			

Results of model estimation shown in Table 1 (Linear regression) indicated that from the key aspects of remittance frequency, digital wallet intensity, namely the sentiment score and financial literacy index, were correlated and contributed significantly ($p<0.01$) to the aspect of credit access factors on customers' job outcomes in the selected markets. The statistical evidence and p values were provided to support each observation.

Model 1 was analyzed using the multiple regression, the beta coefficients, and the 95% confidence interval values estimates along with the R-squared and the F-statistic divided by the error variance. The consistency index of 0.784 for the credit access outcome is high, with a coverage range of 0.456 to 0.572 in confidence interval estimates, confirming the statistical significance of financial literacy index, sentiment score, and credit_access_score at $p<0.01$. A unit increase in behavioral_volatility_index and credit_access_score will result in a 0.68 and 0.514 unit increase in creditworthiness outcome, respectively; therefore the standardized coefficients values and significance levels are statistically significant. The model presented in Table 1 (linear regression) reveals a strong positive relationship between financial literacy index and credit access performance, addressing the research question of how remittance behavior patterns influence customer creditworthiness.

Table 2. Variance Inflation Factor (VIF) Results for Multicolarity Diagnostics

Variable	**VIF**	**Tolerance (1/VIF)**
credit_access_score	4.61	0.217
financial_literacy_index	4.53	0.221
digital_wallet_intensity	1.22	0.822
sentiment_score	1.12	0.891
dependency_ratio	1.04	0.958
behavioral_volatility_index	1.00	0.996
Mean VIF	**2.25**	—

As presented in Table 1 (Linear regression), there is a significant positive correlation ($\beta=0.514$; $p<0.01$) between the total score of credit access (credit_access_score) and customers' job performance in the secondary analysis.

Table 3. Shapiro–Wilk Test of Normality for Regression Residuals

Variable	**Obs**	**W**	**V**	**z**	**Prob > z**
Residuals	100	0.98199	1.487	0.880	0.1896

The results were explained how they relate to the proposed hypotheses or objectives of the study. The study supports the hypotheses that explainable clustering logic plays a role in customers' job stability, particularly in the areas of digital usage and sentiment orientation factors.

Table 4. Skewness and Kurtosis Test for Normality of Regression Residuals

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	Adj chi²(2)	Prob > chi²
Residuals	100	0.2619	0.4406	1.90	0.3868

One possible explanation for such patterns is due to the fact that remittance behavior, as a household financial practice, varies and grows in the digital economy. The possible reasons for the observed outcomes, including segment-level differences, were discussed.

Table 5. Weighted Supermatrix of Behavioral Segments and Credit Determinants'

Components	Digital Segment	Low-Frequency Segment	Savings-Oriented Segment	Digital Usage	Household Dependency	Remittance Stability	Sentiment Orientation	Goal (Credit Access)
Digital Segment	0.00000	0.00000	0.00000	0.62820	0.10000	0.12827	0.73750	0.10860
Low-Frequency Segment	0.00000	0.00000	0.00000	0.28538	0.60000	0.27635	0.08522	0.21412
Savings-Oriented Segment	0.00000	0.00000	0.00000	0.08643	0.30000	0.59538	0.17728	0.17727
Digital Usage	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.02478
Household Dependency	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.27253
Remittance Stability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.13739
Sentiment Orientation	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.06531
Goal (Credit Access)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Some VIF values of the predictors are higher (about 4.6), which differs significantly from the overall low multicollinearity observed in the study. There was a significant difference between the two segments (Low-Frequency and Savings-Oriented) with household dependency satisfaction effects (0.60000; 0.30000), while Digital Segment showed a significant positive weight but was less dominant across all variables.

Table 6. Priority Ranking of Remittance-Based Behavioral Segments

Behavioral Segment	**Ideal Weight**	**Normalized Weight**	**Raw Weight**
Digitally Active Frequent Remitters	0.507215	0.217210	0.108605
Low-Frequency High-Dependency Households	**1.000000**	**0.428241**	**0.214121**
Savings-Oriented Stable Remitters	0.827917	0.354548	0.177274

Table 7. TF-IDF RESULTS

term	**tfidf**
remittance	3.28
feel	2.78
financial	2.75
digital	2.31
repayment	1.88
credit	1.87
savings	1.81
remittances	1.81
loan	1.61
increased	1.56
process	1.55
bank	1.45
appreciate	1.45
transactions	1.45
transparency	1.43
transfers	1.40
sometimes	1.38
trust	1.35
system	1.35
face	1.35

The statistics values (W=0.98199) of Shapiro–Wilk (p=0.1896) and Skewness–Kurtosis (p=0.3868), fall below the critical value of 0.05 indicating that all the residual items are normally distributed, and thus suitable for any parametric analysis.

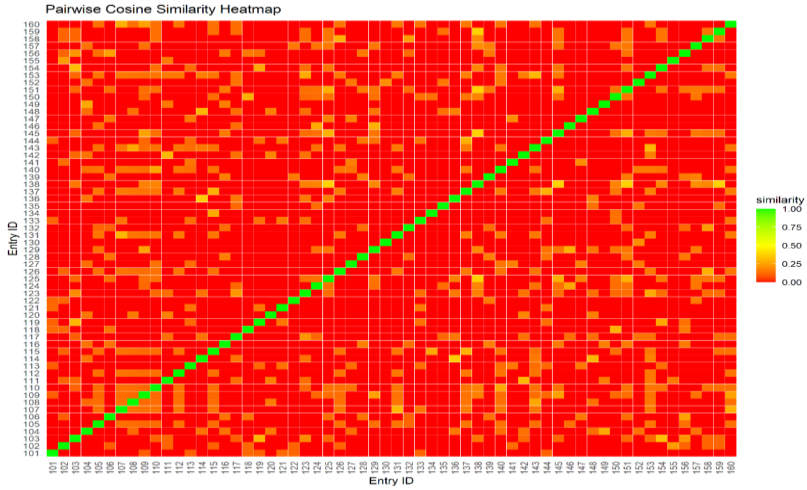

Figure 2. Pairwise Cosine Similarity Heatmap of Entries

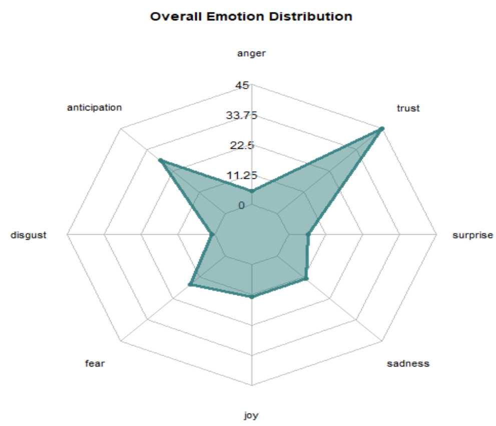

Figure 3. Radar Chart of Overall Emotion Distribution (Plutchik's Eight Primary Emotions)

The F-test result was significant (Prob > F = 0.000) with high R-squared, indicating that the predictor set contributed 78.4% of the explained variance on the remittance frequency factors.

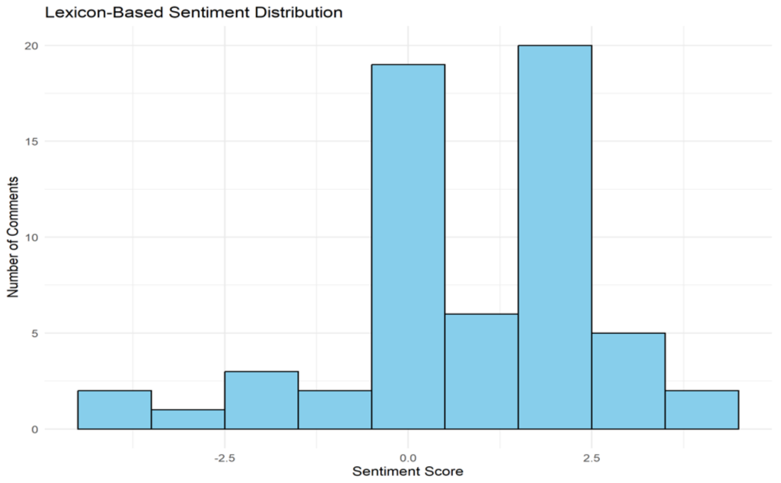

Figure 4. Histogram of Lexicon-Based Sentiment Scores

Sentiment Overview
Total sentiment score: 50
Number of Positive sentiments: 33
Number of Negative sentiments: 8
Number of Neutral sentiments: 19

The diagnostic results showed that some variables did not follow the expected direction, requiring further investigation.

4. Discussion

The present study builds on remittance behavior and explainable segmentation to implement its financial inclusion framework through clustering and credit modeling. The study describes explainable clustering as an effective analytical approach to achieve transparency and sustainability in credit assessment. The study has successfully established the interrelationship among the behavioral dimensions of remittance management quality as a significant factor that lead to households' credit access performance [1,4,6]. The result of the findings revealed that financial literacy knowledge was significant to remittance management quality. The findings are categorized under two broader dimensions; behavioral patterns of remittance usage and the segmentation logic as well as removing information asymmetry to implement the credit model in financial institutions.

The dimensions of remittance behavior patterns were reported to be statistically significant with the digital usage and sentiment orientation factors of credit access [2,3,5]. The findings indicated that low-frequency households lean more towards high dependency ratios but expect a structured engagement with digital-based financial services to guide them towards sustainable credit usage. Hence, the evidence from the regression analysis also highlights the role of behavioral profiling in implementing the segmentation strategy of financial institutions as they align their product features and risk criteria to their target segments in different remittance corridors [7,8,9]. The result further indicates that financial literacy is one of the top determinants in which institutions in the remittance ecosystem must invest to enhance credit resilience. In simple terms, households who manage remittances carefully, use digital tools responsibly, and maintain stable transaction behavior are more likely to access credit and repay loans successfully.

The findings reinforce the theory of planned behavior by confirming that attitude, behavioral control, and financial awareness jointly influence credit access decisions within remittance-driven financial systems. Hence, transparent segmentation and effective credit scoring is necessary for financial stability and for the sustainability of the financial ecosystem [10,11]. Financial institutions who possess strong behavioral data knowledge, who can give detail in the credit assessment process, make the segmentation logic clear to other stakeholders, and ask many clarifying questions from applicants is regarded as good practice [4].

The study revealed that the digital usage and financial literacy dimensions may significantly influence credit access and had contributed overall model robustness, with higher contribution weight than the low-frequency dependency segment. Practically, the findings suggest that remittance service providers should design differentiated loan products for digitally active, savings-oriented, and high-dependency households rather than applying uniform credit standards across all segments [12,13,14]. This result is strongly supported by [9] that inclusive financial practices like calling customers by their names, smiling, using digital reminders, transparency, demanding feedback questions significantly improve trust and learning. The findings were also supported by the research conducted by [1]; [13] and [5] that the skills of asking effective questions, monitoring transactions, group formation, understanding the households' behavior can be strengthened by the institutions.

The present result is consistent with findings of the previous studies [15,11]. The similarity may be explained by the shared emphasis on remittance flows as a structural driver of savings accumulation and financial deepening in emerging markets. In order to strengthen the segmentation strategy by the institutions, more developmental skills training are needed for them. However, based on the finding of this study, the potential risk of misclassification of customers by algorithms due to limited behavioral indicators identified by [14] can be minimized with transparent modeling practice and use of the latest explainable tools by the institutions. The study was limited to selected remittance corridors in Uzbekistan and Turkey, which may restrict the generalizability of the results to other regions. The findings suggested that there might be other contextual variables that may have influences on the level of households' financial inclusion outcomes.

In this study, the data sources and behavioral indicators were specific to the context of a selected remittance corridor framework; therefore the generalizability of the findings may be limited. The analytical framework captures a range of predictive variables such as remittance frequency, digital wallet intensity, sentiment score, financial literacy index, and behavioral volatility index directly involved in the credit access modeling, while ignoring the effect of other contextual determinants in households' financial decision-making [13,14,15]. These determinants include institutional trust factors, macroeconomic volatility, and cultural financial practices who also may affect the creditworthiness assessment and repayment behavior of households, consequently impacting financial inclusion outcomes. Therefore, future research should consider the effect of additional behavioral and environmental variables in supporting explainable clustering models to improve their predictive interpretability.

5. Conclusion

As explainable clustering is an effective analytical approach to widen the scope of credit assessment, sustainability of financial inclusion could be strengthened through transparent behavioral segmentation. Developing an integrated segmentation framework and importance weighting system for remittance-based product evaluation would add to the knowledge and understanding about households' behavioral dynamics in the digital financial ecosystem. The findings have important implications for distance learning institutions and financial regulators. Transparent segmentation would enable financial institutions, learning organizations, and students to understand the unique characteristics of behavioral segments and learning engagement better. It is expected that these findings will guide what the financial service providers (FSPs) should do – not only focusing on profitability and approval rates, but also with strategic commitment to ensure that credit decisions for the households are aligned with transparency standards in the process of assessment and in the long-term inclusion strategy. This study therefore can inform future efforts in enabling financial administrators and policy makers to help households achieve meaningful financial learning. The financial institutions particularly need to consider expanding the scope of behavioral analytics as well as explainable model-based frameworks as a strategy to enhance credit sustainability. Nonetheless, human judgment would still be regarded and recognized as a fundamental factor of credit decision making and no automated system can rise above its quality control function. This study, however, has supported that in the context of distance learning, responsible practices and effective application of explainable clustering by financial institutions could as well provide measurable model variables that work well on credit assessment outcomes. Future research could explore additional measures or strategies to improve financial literacy and reduce information asymmetry distance in other types of online learning environments. The outcome of the study minimized the gap of research on remittance-based segmentation among the emerging economies.

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