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PAPER

M-LAT Acceptance and Decision-Making in Chongqing Secondary Schools: Urban-Rural Perspectives

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ABSTRACT

Mobile-accessible Learning Analytics Technology (M-LAT) offers valuable tools for data-driven educational decision-making, yet its acceptance varies across educational contexts. This study examines factors influencing M-LAT acceptance among secondary school teachers in Chongqing, China, and investigates its relationship with teaching decision-making. Data collected from 341 teachers (197 urban, 144 rural) revealed moderately high overall M-LAT acceptance ($M = 3.68$, $SD = 0.79$), with significant urban-rural differences. Structural equation modelling identified associations between M-LAT acceptance and professional development ($\beta = 0.624$), administrative support ($\beta = 0.581$), and mobile technology infrastructure ($\beta = 0.537$). M-LAT utilisation correlated with teaching decision-making efficacy ($r = 0.578$), with a stronger relationship among urban teachers ($r = 0.612$) than rural counterparts ($r = 0.524$). These findings highlight an urban-rural digital divide and provide evidence for enhancing mobile learning analytics implementation in secondary education.

KEYWORDS

mobile learning analytics, technology acceptance, secondary education, decision-making, urban-rural digital divide

1 INTRODUCTION

The recent spread of mobile technologies and data-driven pedagogy has revolutionised modern education. Mobile Learning Analytics Technology (M-LAT) is the convergence of pedagogical innovation, mobile computing, and educational data science, which provides teachers with previously unimaginable access to actionable knowledge regarding students' learning processes [1]. In China's dynamically changing education environment, M-LAT has become a vital means of improving teachers' effectiveness as well as enabling informed decision-making [2].

M Learning Analytics Technology offers teachers real-time, accessible methods for collecting, analysing, and interpreting learner data by means of mobile-enabled interfaces, making possible instructional decision-making anywhere, anytime [3].

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Recent developments in mobile technology-based learning analytics have demonstrated significant potential for enhancing educational assessment and data-driven instruction [37]. Learning analytics is "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it takes place" [4]. The mobile element infuses these functionalities with flexibility and immediacy, enabling teachers to tap into data-driven information outside the limits of school computer labs or back offices [5].

China's "Action Plan for Education Informatisation 2.0" instituted a holistic strategy for technological integration in education, with a focus on data-driven innovation as well as mobile-based learning solutions [6]. This policy measure supplies both the practical necessity as well as the regulatory framework for M-LAT adoption in Chinese schools. Yet, even with this favourable policy environment, practical M-LAT implementation in China's secondary schools is faced with many difficulties, especially in terms of teachers' acceptance as well as effective use [7]. Recent research has identified multiple factors that influence teachers' willingness to adopt mobile technologies, including technological competence and institutional support [38].

1.1 Research problem and gap

While educational technology has gained significant attention in research, there remains a critical knowledge gap regarding mobile learning analytics, specifically in secondary education contexts in China. Previous studies have predominantly focused on general educational technology adoption [8, 9], higher education settings [10], or Western educational contexts [11].

Several research gaps warrant attention. First, although learning analytics has been extensively studied in higher education [12], limited research has examined its implementation specifically in secondary education contexts in emerging economies [13]. Second, while previous studies have documented urban-rural disparities in general technology access [14], systematic investigation of how these disparities affect M-LAT acceptance and utilisation remains limited. Third, the connection between M-LAT acceptance and concrete educational outcomes—particularly teaching decision-making processes—has not been sufficiently explored in empirical research [15]. While recent studies have examined mobile learning analytics applications in educational assessment [37], the relationship between technology acceptance and teaching effectiveness remains underexplored.

The urban-rural digital divide represents a significant barrier to equitable M-LAT implementation in China. As documented by Wang et al. [16], substantial disparities exist in educational technology infrastructure, teacher training opportunities, and institutional support between urban and rural regions. These disparities are particularly pronounced in Chongqing, a municipality that encompasses both a highly developed urban centre and extensive rural districts [17].

1.2 Research objectives and significance

To address these limitations in current literature, this study pursues two primary research objectives:

- To identify key factors (professional development, administrative support, mobile technology infrastructure and peer influence) influencing M-LAT acceptance

among secondary school teachers in Chongqing, with particular attention to potential urban-rural differences.
- To examine the relationship between M-LAT acceptance and teaching decision-making efficacy, determining how this relationship varies across urban and rural educational settings.

This study contributes to the existing literature in several ways. First, it provides empirical evidence on M-LAT acceptance specifically in secondary education contexts, addressing a notable gap in current research. Second, it offers a detailed analysis of the urban-rural digital divide in M-LAT implementation, contributing to broader discussions about educational equity in technology integration. Third, it examines the concrete impact of M-LAT on teaching decision-making processes, linking technology acceptance to tangible educational outcomes.

2 THEORETICAL FRAMEWORK

This study employs an integrated theoretical framework combining three complementary theories to comprehensively understand M-LAT acceptance and its relationship with teaching decision-making in Chinese secondary schools.

2.1 Technology acceptance model

The technology acceptance model (TAM) [18] provides the foundational framework for understanding individual-level technology adoption. TAM posits that technology adoption is primarily determined by two key beliefs: perceived usefulness (PU) and perceived ease of use (PEOU). In educational contexts, TAM has been extended to include pedagogical considerations, suggesting that teachers' acceptance depends not only on technical factors but also on perceived educational value and instructional integration ease [21].

For M-LAT acceptance, TAM helps explain why teachers may recognise learning analytics' potential value (cognitive attitudes) yet struggle with implementation (actual use). The model's emphasis on belief-behaviour relationships is particularly relevant for understanding the intention-behaviour gap commonly observed in educational technology adoption.

2.2 Unified theory of acceptance and use of technology

Unified theory of acceptance and use of technology (UTAUT) [19] extends TAM by incorporating contextual and social factors that influence technology acceptance. The model identifies four key determinants: (1) performance expectancy, (2) effort expectancy, (3) social influence, and (4) facilitating conditions. Additionally, UTAUT recognises that individual characteristics (age, gender, and experience) and contextual factors moderate these relationships.

In this study, UTAUT contributes by addressing the social and organisational dimensions of M-LAT acceptance. The model's emphasis on facilitating conditions is particularly relevant for understanding urban-rural differences, as infrastructure and support systems vary significantly between these contexts. UTAUT's inclusion of social influence also helps explain the role of peer networks and administrative support in technology adoption.

2.3 Data-driven decision-making theory

Data-driven decision-making theory [20] provides the framework for understanding how M-LAT acceptance translates into improved teaching practices. This theory conceptualises effective decision-making as a four-stage process: (1) data collection, (2) data analysis, (3) interpretation of findings, and (4) implementation of evidence-based actions.

The theory suggests that M-LAT enhances this process by providing timely, accessible, and actionable information that improves both the efficiency and quality of educational decisions. This theoretical lens helps explain why M-LAT usage correlates with teaching decision-making efficacy and provides a framework for understanding the mechanisms through which learning analytics improves instructional practice.

2.4 Integrated framework

Our integrated framework posits that while TAM explains individual cognitive and behavioural responses to M-LAT, UTAUT illuminates the contextual factors that enable or constrain adoption, and data-driven decision-making theory elucidates the educational outcomes of successful implementation (see Figure 1).

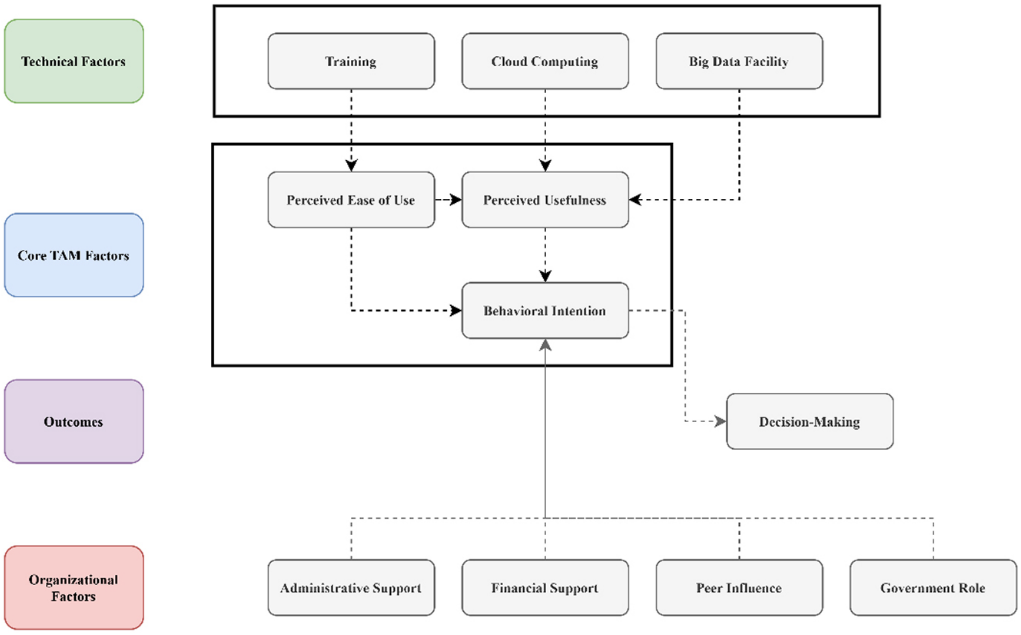

Fig. 1. Extended TAM model for mobile learning analytics in urban and rural educational settings

3 METHODOLOGY

3.1 Research design

This study employed a quantitative cross-sectional research design to investigate M-LAT acceptance among secondary school teachers in Chongqing, China. Quantitative methodology was selected for its capacity to measure variables systematically, examine relationships between constructs, and produce generalisable findings [22]. The cross-sectional approach enabled data collection at a specific point in time, providing a snapshot of current M-LAT acceptance patterns and their relationship with teaching decision-making practices.

A quantitative approach was deemed appropriate based on several considerations. First, the research objectives focused on examining predictive relationships between variables and comparing group differences, which aligns with quantitative methodological strengths. Second, established measurement instruments existed for key constructs, facilitating reliable and valid quantitative assessment. Third, the study aimed to produce generalisable findings that could inform educational policy, requiring a representative sample and statistical analysis approach.

3.2 Population and sampling

The target population comprised secondary school teachers in Chongqing municipality, China. According to the Chongqing Education Commission, approximately 2,997 teachers were employed across 18 major secondary schools in the region at the time of study. Using Krejcie and Morgan's [23] sample size determination formula, a sample of 341 teachers was required to achieve a confidence level of 95% with a 5% margin of error.

Proportional stratified random sampling was employed to ensure representative participation from both urban and rural schools. Schools were first categorised as either urban (n = 10) or rural (n = 8) based on their geographical location and administrative designation. Teachers were then randomly selected from each stratum in proportion to their representation in the total population. This sampling strategy resulted in 197 participants from urban schools and 144 from rural schools.

3.3 Research instrument

The research instrument was developed based on established measures in the technology acceptance and educational data analytics literature. The questionnaire was structured into four main sections to comprehensively assess the study variables:

The final questionnaire comprised four sections:

1. Demographic Information: Items capturing participants' gender, age, teaching experience, educational qualifications, and school type.
2. M-LAT Acceptance Scale: A 15-item measure assessing three dimensions of technology acceptance: cognitive attitudes (5 items), behavioural intentions (5 items), and actual use (5 items). All items utilised a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).
3. Influencing Factors Scale: A 20-item measure examining four potential determinants of M-LAT acceptance: professional development (5 items), administrative support (5 items), mobile technology infrastructure (5 items), and peer influence (5 items). All items employed a 5-point Likert scale.
4. Teaching Decision-Making Scale: A 10-item measure evaluating two dimensions of teaching decision-making: decision-making process (5 items) and decision quality (5 items). All items utilised a 5-point Likert scale.

Since the instrument was adapted from multiple established scales, confirmatory factor analysis (CFA) was conducted to verify the underlying structure and validate the measurement model. The CFA results demonstrated excellent fit indices with all factor loadings exceeding .70 and strong internal consistency reliability across all scales (refer to Table 1).

Table 1. Confirmatory factor analysis results for the M-LAT instrument (N = 341)

Category	Results
Model Fit Indices	
χ^2 (df)	846.329 (783)
χ^2/df	1.081
p-value	.057
CFI	.984
TLI	.981
RMSEA [90% CI]	.031 [.022, .042]
SRMR	.035
GFI	.926
Standardized Factor Loadings	
Cognitive Attitudes (CA1–CA5)	.810–.854
Behavioural Intentions (BI1–BI5)	.795–.831
Actual Use (AU1–AU5)	.837–.889
Professional Development (PD1–PD5)	.814–.843
Administrative Support (AS1–AS5)	.785–.823
Mobile Technology Infrastructure (MTI1–MTI5)	.763–.814
Peer Influence (PI1–PI5)	.753–.783
Decision-Making Process (DMP1–DMP5)	.780–.817
Decision Quality (DQ1–DQ5)	.805–.844
Inter-Factor Correlations	.482–.734
Variance Explained (R^2)	.567–.791

Notes: All factor loadings are significant at $p < .001$. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; CI = Confidence Interval; SRMR = Standardized Root Mean Square Residual; GFI = Goodness of Fit Index.

The CFA results confirmed the expected factor structure with excellent fit indices. The ratio of chi-square to degrees of freedom (χ^2/df = 1.081) was well below the recommended threshold of 3.0, and the p-value of .057 indicated that the model was not significantly different from the data. The CFI (.984) and TLI (.981) values both exceeded the recommended threshold of .95, indicating excellent fit. The RMSEA value of .031 (90% CI [.022, .042]) and SRMR of .035 were both below .06, further confirming excellent model fit.

All items loaded significantly on their respective factors with standardised loadings ranging from .753 to .889, well above the recommended threshold of .70. The inter-factor correlations ranged from .482 to .734, indicating related but distinct constructs. The variance explained (R^2) for individual items ranged from .567 to .791, demonstrating good explanatory power. The instrument also demonstrated strong internal consistency reliability as evaluated using Cronbach's alpha coefficients (refer to Table 2).

Table 2. Cronbach's alpha reliability coefficients for study constructs

Construct	Number of Items	Cronbach's Alpha
Cognitive Attitudes	5	0.892
Behavioural Intentions	5	0.875
Actual Use	5	0.903
Professional Development	5	0.881
Administrative Support	5	0.864
Mobile Technology Infrastructure	5	0.837
Peer Influence	5	0.825
Decision-Making Process	5	0.849
Decision Quality	5	0.878

All Cronbach's alpha values exceeded the recommended threshold of 0.70, indicating excellent reliability across all scales. Convergent validity was established as all average variance extracted (AVE) values were above the recommended threshold of 0.50, ranging from 0.596 to 0.748. Discriminant validity was also confirmed as the square root of the AVE for each construct was greater than its correlation with any other construct.

3.4 Data collection procedures

Following approval from the Chongqing Education Commission and the university research ethics committee, data collection was conducted over a two-month period (March–April 2023). The questionnaire was distributed in both paper and electronic formats to maximise response rates. Participation was voluntary, and all respondents provided informed consent before completing the questionnaire.

The data collection yielded 352 completed questionnaires, of which 341 were deemed valid after excluding incomplete responses, resulting in a 96.9% effective response rate. Data quality was ensured through careful screening for missing values, response patterns, and outliers before proceeding with analysis.

3.5 Data analysis

The data analysis methods were carefully aligned with the research questions to ensure that appropriate analytical techniques were employed to address each specific research objective. For the first research question examining the current level of M-LAT acceptance among secondary school teachers in Chongqing, descriptive statistics (means and standard deviations) were utilised to provide a baseline understanding of acceptance levels across different dimensions.

To investigate significant differences in M-LAT acceptance between urban and rural teachers, independent samples t-tests with effect size calculations were employed. For identifying factors influencing M-LAT acceptance among secondary school teachers, structural equation modelling (SEM) with path analysis was implemented. The relationship between M-LAT usage and teaching decision-making efficacy was investigated using Pearson correlation analysis, complemented by partial correlations.

Statistical significance was established at $p < 0.05$ for all analyses. Effect sizes were calculated to assess the practical significance of statistical findings, using Cohen's d for group comparisons and standardised path coefficients for structural relationships.

4 RESULTS

4.1 Participant characteristics

The demographic composition of the 341 valid respondents is presented in Table 3. Female teachers constituted 56.3% (n = 192) of the sample, while male teachers represented 43.7% (n = 149). The age distribution showed that 19.6% (n = 67) were under 30 years, 42.8% (n = 146) were 31–40 years, 28.2% (n = 96) were 41–50 years, and 9.4% (n = 32) were over 50 years. Regarding teaching experience, 15.8% (n = 54) had less than five years, 26.7% (n = 91) had 6–10 years, 31.1% (n = 106) had 11–15 years, and 26.4% (n = 90) had over 16 years.

Table 3. Demographic characteristics of participants

Characteristic	Category	Frequency	Percentage (%)
Gender	Female	192	56.3
	Male	149	43.7
Age (years)	Under 30	67	19.6
	31–40	146	42.8
	41–50	96	28.2
	Over 50	32	9.4
Teaching Experience (years)	0–5	54	15.8
	6–10	91	26.7
	11–15	106	31.1
	Over 16	90	26.4
School Type	Urban	197	57.8
	Rural	144	42.2

Chi-square analysis revealed no significant differences in gender distribution between urban and rural sub-samples ($\chi^2 = 2.13$, $p = 0.144$). However, significant differences were observed in age distribution ($\chi^2 = 9.27$, $p = 0.026$) and teaching experience ($\chi^2 = 8.84$, $p = 0.032$), with rural schools having slightly higher proportions of older and more experienced teachers.

4.2 Measurement model assessment

Confirmatory factor analysis was conducted to assess the measurement model before proceeding with structural analysis. The measurement model demonstrated acceptable fit to the data: $\chi^2/df = 2.17$, CFI = 0.931, TLI = 0.924, RMSEA = 0.059, SRMR = 0.048. All standardised factor loadings exceeded 0.60 and were statistically significant ($p < 0.001$), indicating strong relationships between observed variables and their respective latent constructs.

4.3 M-LAT acceptance status

Descriptive statistics for teachers' M-LAT acceptance are presented in Table 4. The results indicate that teachers' overall acceptance of M-LAT was moderately high (M = 3.68, SD = 0.79). Among the three dimensions, cognitive attitudes scored highest (M = 3.85, SD = 0.67), followed by behavioural intentions (M = 3.78, SD = 0.72), while actual use scored lowest (M = 3.41, SD = 0.93). This pattern suggests that teachers recognise the value of M-LAT and express willingness to use it but face challenges in implementing it in their actual teaching practice.

Table 4. Descriptive statistics of teachers' M-LAT acceptance

Dimension	Mean	Standard Deviation	Level
Cognitive Attitudes	3.85	0.67	High
Behavioural Intentions	3.78	0.72	High
Actual Use	3.41	0.93	Moderate
Overall Acceptance	3.68	0.79	Moderately High

Item-level analysis revealed that within the cognitive attitudes dimension, teachers most strongly endorsed statements regarding M-LAT's potential to enhance data accessibility (M = 4.12, SD = 0.63) and improve instructional decision-making (M = 4.05, SD = 0.71). Within the behavioural intentions dimension, intentions to increase future M-LAT usage (M = 3.92, SD = 0.68) received the highest endorsement. Within the actual use dimension, using M-LAT for student performance monitoring (M = 3.67, SD = 0.88) was most frequently reported, while using M-LAT for personalised instruction (M = 3.14, SD = 1.07) was least common.

The attitude-behaviour gap (M = 3.85 vs. M = 3.41) contributes to TAM theory by demonstrating that perceived usefulness alone is insufficient for actual use in educational contexts, suggesting TAM requires contextual moderators.

4.4 Urban-rural differences in M-LAT acceptance

Significant differences in M-LAT acceptance were observed between urban and rural teachers, as shown in Table 5. Addressing the first research objective, these findings confirm substantial urban-rural differences in M-LAT acceptance, with the widening gap from attitudes ($d = 0.65$) to actual use ($d = 0.69$) extending TAM theory by demonstrating that contextual factors moderate the attitude-behaviour relationship. This contributes to theory by showing that external constraints can progressively weaken the predictive power of internal acceptance factors. The gap was most pronounced in actual use (urban: M = 3.67, SD = 0.82; rural: M = 3.06, SD = 0.95), suggesting that rural teachers face greater challenges in implementing M-LAT despite recognizing its value. Independent samples t-tests confirmed that these differences were statistically significant across all dimensions ($p < 0.001$).

Table 5. Comparison of M-LAT acceptance between urban and rural teachers

Dimension	Urban Teachers (n = 197)		Rural Teachers (n = 144)		t-value	p-value	Cohen's d
	Mean	SD	Mean	SD			
Cognitive Attitudes	4.02	0.58	3.61	0.69	6.18	< 0.001	0.65
Behavioural Intentions	3.96	0.64	3.53	0.74	5.82	< 0.001	0.63
Actual Use	3.67	0.82	3.06	0.95	6.52	< 0.001	0.69
Overall Acceptance	3.92	0.65	3.44	0.78	6.31	< 0.001	0.67

Effect size analysis using Cohen's d indicated medium to large effects for all urban-rural differences (d ranging from 0.63 to 0.69), highlighting the practical significance of these disparities. Item-level analysis revealed particularly pronounced urban-rural differences in specific aspects of M-LAT use. The largest disparities were observed in using M-LAT for personalised instruction (urban: $M = 3.54$, $SD = 0.97$; rural: $M = 2.62$, $SD = 1.03$; $t = 8.37$, $p < 0.001$, $d = 0.92$) and data-driven classroom adaptations (urban: $M = 3.61$, $SD = 0.88$; rural: $M = 2.78$, $SD = 1.02$; $t = 7.92$, $p < 0.001$, $d = 0.87$).

4.5 Factors associated with M-LAT acceptance

Structural equation modelling was performed to examine the predictive relationships between hypothesised influencing factors and M-LAT acceptance. The structural model demonstrated good fit to the data ($\chi^2/df = 2.36$, CFI = 0.943, TLI = 0.937, RMSEA = 0.058, SRMR = 0.045). As shown in Figure 2 and Table 4, all four hypothesised factors significantly predicted M-LAT acceptance ($p < 0.001$). These findings directly answer the first research objective by identifying four significant predictors, with professional development ($\beta = 0.624$) emerging as the strongest. This extends UTAUT theory by confirming that effort expectancy (through professional development) outweighs facilitating conditions in educational contexts. The rural-urban variation where infrastructure becomes primary in rural areas ($\beta = 0.629$) contributes to theory by demonstrating that predictor hierarchies shift based on environmental constraints (see Figure 2).

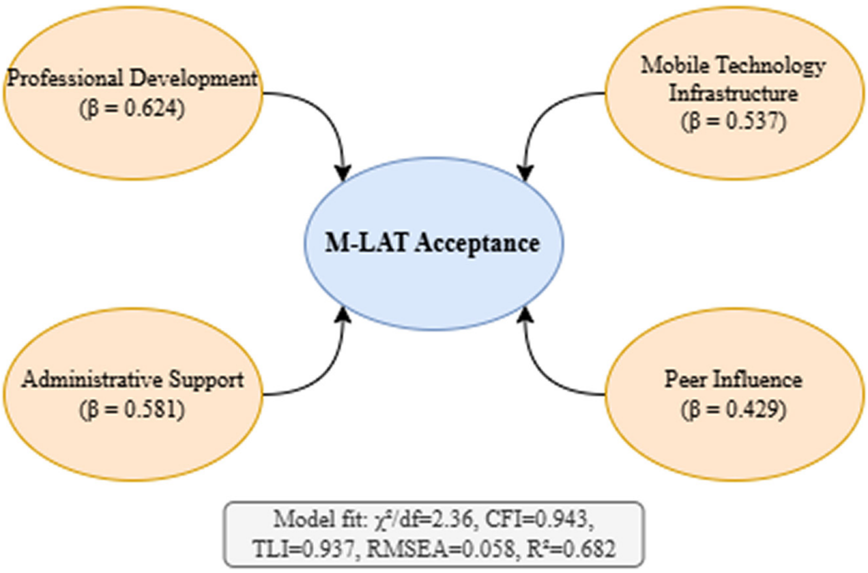

Fig. 2. Path model of factors influencing M-LAT acceptance

Table 6. Standardized regression weights for factors predicting M-LAT acceptance

Predictor	β	SE	t-value	p-value	95% CI
Professional Development	0.624	0.042	14.86	< 0.001	[0.542, 0.706]
Administrative Support	0.581	0.045	12.91	< 0.001	[0.493, 0.669]
Mobile Technology Infrastructure	0.537	0.048	11.19	< 0.001	[0.443, 0.631]
Peer Influence	0.429	0.051	8.41	< 0.001	[0.329, 0.529]

The model explained 68.2% of the variance in overall M-LAT acceptance ($R^2 = 0.682$), indicating substantial explanatory power. Multi-group analysis revealed partial measurement invariance between urban and rural subsamples, allowing for meaningful comparison of structural relationships. The relative influence of predictor variables showed some variation between urban and rural contexts. In urban schools, professional development ($\beta = 0.647$, $p < 0.001$) and administrative support ($\beta = 0.603$, $p < 0.001$) demonstrated the strongest influence. In rural schools, mobile technology infrastructure ($\beta = 0.629$, $p < 0.001$) emerged as the most influential factor, followed by professional development ($\beta = 0.592$, $p < 0.001$).

Further analysis of the relationships between specific M-LAT acceptance dimensions and influencing factors revealed that professional development had the strongest association with behavioural intentions ($\beta = 0.648$, $p < 0.001$), while mobile technology infrastructure showed the strongest relationship with actual use ($\beta = 0.562$, $p < 0.001$). These findings suggest that different factors may influence distinct aspects of technology acceptance, with infrastructure particularly critical for translating positive attitudes into actual usage behaviour.

The 68.2% variance explained by institutional factors advances UTAUT theory by confirming that organizational variables outweigh individual preferences in educational technology adoption.

4.6 M-LAT usage and teaching decision-making

Correlation analysis was conducted to examine the relationship between M-LAT usage and teaching decision-making dimensions. As shown in Table 7, addressing the second research objective, the strong M-LAT-decision making correlation ($r = 0.578$) provides empirical support for data-driven decision-Making theory's core proposition that analytics enhance educational outcomes. The stronger relationship with decision quality ($r = 0.594$) versus process ($r = 0.536$) contributes to theory by specifying that analytics improve decision outcomes more than procedures. The urban-rural moderation ($r = 0.612$ vs. $r = 0.524$) extends theory by showing that technology benefits are contextually dependent. The correlation with overall decision-making efficacy was strong ($r = 0.578$), with a slightly stronger association with decision quality ($r = 0.594$) than with the decision-making process ($r = 0.536$). These findings suggest that teachers who more frequently use M-LAT tend to report higher efficacy in their teaching decision-making, particularly regarding the quality of decisions made (refer to Table 7).

Table 7. Correlations between M-LAT usage and teaching decision-making

Variable	1	2	3	4
1. M-LAT Usage	1.000			
2. Decision-Making Process	0.536***	1.000		
3. Decision Quality	0.594***	0.621***	1.000	
4. Overall Decision-Making Efficacy	0.578***	0.874***	0.918***	1.000

Note: ***$p < 0.001$.

To examine potential confounding variables, partial correlation analysis was conducted, controlling for teaching experience, age, and gender. The correlations remained significant and only slightly reduced in magnitude after controlling for these variables (partial r ranging from 0.498 to 0.572, $p < 0.001$), suggesting that the relationship between M-LAT usage and decision-making efficacy is robust beyond demographic influences.

Item-level analysis revealed that M-LAT usage was most strongly correlated with specific decision-making aspects, including "identifying specific learning needs" ($r = 0.632$, $p < 0.001$), "evaluating instructional effectiveness" ($r = 0.609$, $p < 0.001$), and "implementing timely interventions" ($r = 0.587$, $p < 0.001$). These findings indicate that M-LAT particularly enhances teachers' ability to identify student needs, evaluate teaching effectiveness, and implement responsive interventions.

4.7 Urban-rural differences in the M-LAT-decision-making relationship

Additional correlation analysis was conducted to examine potential differences in the relationship between M-LAT usage and teaching decision-making between urban and rural teachers. As shown in Table 8, the correlation between M-LAT usage and overall teaching decision-making efficacy was stronger among urban teachers ($r = 0.612$, $p < 0.001$) than rural teachers ($r = 0.524$, $p < 0.001$). Fisher's r-to-z transformation confirmed that this difference was statistically significant ($z = 2.18$, $p = 0.029$), indicating that urban teachers derive greater decision-making benefits from M-LAT usage compared to their rural counterparts (refer to Table 8).

Table 8. Urban-rural differences in the M-LAT-decision-making relationship

Relationship	Urban Teachers (n = 197)	Rural Teachers (n = 144)	z-value	p-value
M-LAT Usage – Decision-Making Process	0.573***	0.487***	1.86	0.063
M-LAT Usage – Decision Quality	0.632***	0.538***	2.14	0.032
M-LAT Usage – Overall Decision-Making	0.612***	0.524***	2.18	0.029

Note: ***$p < 0.001$.

The urban-rural difference was particularly pronounced for the relationship between M-LAT usage and decision quality (urban: $r = 0.632$; rural: $r = 0.538$; $z = 2.14$, $p = 0.032$), while the difference in the relationship with the decision-making process was marginally significant (urban: $r = 0.573$; rural: $r = 0.487$; $z = 1.86$, $p = 0.063$).

These findings suggest that urban-rural disparities are more substantial in how M-LAT enhances decision outcomes rather than procedural aspects of decision-making.

The differential correlation strength challenges the universality assumption in data-driven decision-making theory, contributing the insight that contextual factors moderate the analytics-performance relationship.

5 DISCUSSION

5.1 Current state of M-LAT acceptance

The moderately high overall M-LAT acceptance (M = 3.68) observed in this study aligns with previous research by Teo et al. [21], which found generally favourable attitudes toward educational technology among Chinese teachers. However, the notable disparity between cognitive attitudes (M = 3.85) and actual use (M = 3.41) reveals a significant implementation gap. This cognitive-behavioural gap implies that teachers perceive the value in M-LAT but face enormous hurdles in their implementation in their day-to-day teaching.

This implementation gap coincides with the so-called "intention-behaviour gap" reported by Liu et al. [8] in their technology acceptance study among Chinese language teachers. This continued gap between attitudes and behaviour implies that technology implementation strategies emphasizing mainly attitudinal change will not be effective. Effective technology integration demands holistic strategies that target not just cognitive and motivational factors but also practical implementation hindrances as well as contextual constraints [24].

5.2 Urban-rural digital divide

The noteworthy urban-rural differences in M-LAT acceptance shown here are indicative of greater inequalities in educational technology adoption and implementation throughout China. Urban teachers exhibited persistently higher acceptance on each measure, with the difference widest on actual use (urban: M = 3.67; rural: M = 3.06). These results are commensurate with those of Samane-Cutipa et al. [26], who reported extensive urban-rural differences in educational technology use across developing regions.

The size of the urban-rural gap differed by dimensions of M-LAT acceptance, with widest disparities in actual use as opposed to intention or attitude. This trend implies rural teachers are aware of the possible value of M-LAT and are willing to employ it but are subject to disproportionate implementation challenges relative to urban teachers. Rural schools tend to be subject to compounding technology implementation disadvantages such as technological infrastructure limitations, fiscal constraints, as well as insufficient professional support [27].

5.3 Key factors influencing M-LAT acceptance

Structural equation modelling showed professional development (β = 0.624) as the most powerful predictor of M-LAT acceptance, followed by administrative support (β = 0.581), mobile technology infrastructure (β = 0.537), and peer influence (β = 0.429). These findings are consistent with past studies on educational technology adoption and evidence the complex nature of technology acceptance in academic environments, aligning with recent findings on factors that influence teachers' willingness to adopt mobile technologies [38].

The intense professional development impact on M-LAT acceptance highlights the decisive role played by teacher training in stimulating educational technology integration. This finding is consistent with research demonstrating that mobile-based professional development programs can effectively enhance teachers' technological competencies and acceptance [39]. This result is corroborated by a study by Dahri et al. [29], which concluded that extensive technology education greatly facilitates technology acceptance among teachers by enhancing both technology skills and pedagogy. The very strong correlation of professional development with behavioural intentions ($\beta = 0.648$) implies that intensive training not only establishes technological expertise but also reinforces teachers' intention and commitment towards technology integration.

Mobile technology infrastructure exhibited a highly positive correlation with actual M-LAT use ($\beta = 0.562$), reaffirming the key role technology requirements play in effective implementation. This result is supported by findings from Mustafa et al. [30], who also listed infrastructure quality as a key requirement to turn positive technology attitudes into persistent habits. The differential relative impact of infrastructure, being highest in rural environments, further attests to its pivotal role in technology adoption, especially where technology resources are limited.

Administrative support came out as the second strongest predictor of M-LAT adoption, emphasizing the central position of school leadership in technology adoption. This is buttressed by a study by Esteve-Mon et al. [31], which cited institutional leadership as a key driver for educational technology adoption. Administrative support involves a number of factors such as ensuring resources, formulating policies, and incentive systems, as well as leadership in building the kind of organizational climate that supports technology integration.

5.4 M-LAT and teaching decision-making

The strong positive correlation between M-LAT usage and teaching decision-making efficacy ($r = 0.578$) provides empirical support for the theoretical proposition that learning analytics enhances educational decision-making. The slightly stronger association with decision quality ($r = 0.594$) compared to the decision-making process ($r = 0.536$) suggests that M-LAT particularly enhances the substantive outcomes of decisions rather than merely facilitating the procedural aspects of decision-making.

These findings align with research by Kaushik and Agrawal [32], which found that learning analytics technologies provide educators with objective, real-time information that improves their ability to identify learning trends and adapt instructional strategies accordingly. The correlation between M-LAT usage and decision quality supports the proposition that data-driven approaches enhance the precision and effectiveness of educational interventions by providing empirical foundations for instructional choices [33].

5.5 Urban-rural differences in the M-LAT-decision-making relationship

The stronger correlation of M-LAT use with effectiveness at the level of urban teachers ($r = 0.612$) in contrast to rural teachers ($r = 0.524$) again stresses the urban-rural educational technology gap in the area of benefits. The reason for this gap could be the varying quality of technology, technical assistance, and information literacy skills [35]. Urban teachers could be provided with more advanced M-LAT tools, improved technical assistance, as well as superior information literacy skills for interpreting the data, allowing them to capture increased gains in terms of making informed decisions through technology.

The starker urban-rural difference in the correlation of M-LAT with decision quality as opposed to the decision—making process implies that rural teachers are especially hindered in converting information insights into effective instructional actions. This corresponds to findings by Sepasgozar [33], who determined that the "response" stage of information-based decision making—converting analytical information into effective instructional interventions—was especially challenging and resource-intensive.

6 IMPLICATIONS AND CONCLUSION

6.1 Theoretical implications

This study contributes to the theoretical literature on educational technology acceptance by integrating insights from the TAM, the UTAUT, and data-driven decision-making theory. The findings confirm the applicability of these theoretical frameworks to the Chinese educational context while highlighting the importance of contextual factors such as urban-rural location in moderating technology acceptance processes.

The multifaceted conception of technology acceptance used in this STUDY—covering cognitive attitude, intentions for use and actual use—develops theoretical analysis by emphasizing the staged, complex nature of technology adoption. The gaps that are observed among these dimensions indicate that technology acceptance must be conceived as a process, as opposed to a single state, with varying factors at work at each stage of the adoption process.

6.2 Practical implications

The conclusions of this study also hold practical implications for all educational stakeholders interested in promoting M-LAT adoption in secondary schools, aligning with recent findings on factors that influence teachers' willingness to adopt mobile technologies [38]. The high correlation of professional development with M-LAT acceptance means that extensive teacher preparation programs must be a priority in technology deployment strategies. Mobile-based professional development approaches have shown particular promise for sustainable teacher training [39]. These programs must cover not just technical competencies but pedagogical uses as well as data interpretation skills to close the gap between positive attitudes and persistent practice.

Professional development efforts must be differentiated according to teacher needs, as well as by context, especially in consideration of urban-rural distinctions. Rural teachers could be helped by special programs that address their specific implementation challenges, such as optimized technology benefits with minimal infrastructure as well as adjusting analysis strategies to small group populations. Mobile-based professional development programs may be particularly effective in addressing resource constraints and access limitations faced by rural educators [39].

Second, the substantial impact of administrative support underscores the need for school leaders' participation in technology implementation efforts. Administrators' professional development must be focused on the potential value of M-LAT to educational performance and on leading the development of organizational cultures in support of technology integration.

Third, the close correlation between mobile technology infrastructure levels and actual M-LAT use demonstrates the necessity of sufficient technical resources as the starting point for effective implementation. Policy efforts must prioritize the building of strong technology infrastructure, especially in rural schools, to address the urban-rural digital divide.

6.3 Limitations and future research

Despite its contributions, this study has several limitations that should be acknowledged. First, the cross-sectional design precludes causal inferences about the relationships between variables. Longitudinal research is needed to examine how M-LAT acceptance evolves over time and how it influences teaching practices and student outcomes in the long term. Second, the reliance on self-report measures introduces potential response biases, including social desirability and retrospective recall biases.

Future research should also investigate the relationship between M-LAT usage, teaching decision-making, and student outcomes to establish the ultimate educational impact of learning analytics implementation. Studies should examine how mobile learning analytics applications in assessment contexts [37] can be integrated with factors that influence teachers' adoption willingness [38] to create comprehensive implementation frameworks. Additionally, intervention studies testing specific strategies for enhancing M-LAT acceptance and effectiveness would provide practical guidance for educational stakeholders seeking to optimize technology implementation.

6.4 Conclusion

This study examined factors influencing M-LAT acceptance among secondary school teachers in Chongqing, China, and investigated the relationship between M-LAT acceptance and teaching decision-making efficacy. The findings revealed moderately high overall M-LAT acceptance, with significant urban-rural disparities across all acceptance dimensions. Professional development, administrative support, mobile technology infrastructure, and peer influence were identified as significant predictors of M-LAT acceptance, with professional development demonstrating the strongest influence. M-LAT usage showed a strong positive correlation with teaching decision-making efficacy, particularly regarding decision quality, with this relationship stronger among urban teachers than rural counterparts.

These findings provide empirical evidence for educational administrators and policymakers seeking to enhance M-LAT implementation in secondary schools. The results suggest that comprehensive approaches addressing professional development, institutional support, and technological infrastructure are essential for effective M-LAT integration. Particular attention should be directed toward reducing urban-rural disparities to ensure equitable distribution of educational technology benefits.

This study provides empirical evidence that M-LAT acceptance is not merely a technology adoption issue but a complex educational equity challenge that intersects with broader urban-rural disparities in Chinese education. The finding that urban teachers not only adopt M-LAT more readily but also derive greater decision-making benefits highlights how technological solutions can inadvertently exacerbate existing inequalities unless implementation strategies explicitly address contextual constraints. Future M-LAT implementation must prioritize context-adaptive strategies that recognize rural schools' unique challenges while building on urban schools' advanced capabilities to create collaborative networks that benefit all learners.

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