THE IMPACT OF DATA-DRIVEN PERSONALIZATION ON THE MARKET EXPANSION OF AI-EDUCATION STARTUPS: THE MEDIATING ROLE OF LEARNING EXPERIENCE OPTIMIZATION AND THE MODERATING EFFECT OF TECHNOLOGICAL INFRASTRUCTURE READINESS

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Abstract: This study explores how data-driven personalization influences the market expansion of AI education startups, highlighting the mediating role of learning experience optimization and the moderating role of technological infrastructure readiness. A theoretical framework was developed incorporating these variables, with empirical data collected from 442 respondents across startups in G Province, China. Using structural equation modeling (SEM), the results confirm that data-driven personalization significantly enhances learning experiences, which in turn drives market expansion. Although learning experience optimization mediates this relationship, the moderating effect of technological infrastructure readiness was not statistically significant. The findings underscore the strategic importance of personalization and user experience design in driving platform growth. This research contributes to the EdTech field by integrating business growth logic with user-centered design and provides actionable insights for startups seeking scalable, sustainable growth in digitally transforming education ecosystems.

Keywords: Data-Driven Personalization, Learning Experience Optimization, Market Expansion, Technological Infrastructure, AI Education

Introduction

The education technology (EdTech) industry is undergoing a profound transformation amid the exponential advancement of Artificial Intelligence (AI), Big Data analytics, and cloud computing infrastructures. AI-powered EdTech startups are rapidly emerging as key players in this landscape, leveraging Data-Driven Personalization (DDP) strategies to revolutionize how educational content is delivered, how learners engage with knowledge, and how platforms grow and scale their services. These startups aim not only to enhance educational outcomes but also to unlock new revenue streams and fuel strategic Market Expansion across diverse user groups and geographic regions (Abdukhalilovich, 2025).

This evolution is part of a broader shift from traditional education systems—characterized by standardized curricula and linear learning paths—toward intelligent, adaptive learning ecosystems. DDP has become central to this shift, offering real-time customization of content, assessments, learning pace, and feedback based on learner behavior, preferences, and performance data. In practice, this involves an integrated application of machine learning algorithms, user modeling, and automated decision systems to create a personalized, end-to-end digital learning journey for each user (Ayodeji, Mensah, & Tan, 2024).

More than a pedagogical enhancement, DDP is now recognized as a business-critical strategy. Research by Kiran and Gopal (2025) shows that personalization significantly improves learner engagement, platform loyalty, and referral behavior. These, in turn, directly contribute to enhanced user acquisition and retention metrics, which are key indicators of Market Expansion potential. Particularly in competitive and saturated digital education markets, startups that deploy sophisticated personalization engines are better positioned to differentiate their services, expand their market presence, and achieve scalability through user data optimization.

Yet, the implementation and effectiveness of DDP are not uniform across all contexts. Technological Infrastructure Readiness (TIR) plays a decisive role in determining whether AI-based personalization strategies can be successfully deployed and adopted. Wah et al. (2025) highlight that cloud availability, device accessibility, platform interoperability, and digital policy ecosystems are crucial determinants of how well DDP systems function in real-world settings. In environments where broadband access is unstable, device penetration is low, or data governance frameworks are weak, even the most advanced personalization algorithms struggle to deliver their intended benefits (Reddy, 2025).

Such disparities are especially salient in emerging markets, where the "last mile" of EdTech deployment remains a significant challenge. In contrast, regions with robust infrastructure not only facilitate smoother implementation but also offer more favorable conditions for collecting, analyzing, and acting on user data—thereby amplifying the benefits of personalization. Therefore, infrastructure maturity becomes a critical moderating factor that can either enhance or inhibit the return on investment from AI-powered learning systems.

At the heart of this interplay between technology and market growth lies the concept of Learning Experience Optimization (LEO). As a mediating variable, LEO serves as the mechanism through which DDP translates into market performance. According to Du (2025), platforms that optimize the learner experience through personalized interfaces, adaptive tasking, gamified feedback, and emotional intelligence features consistently report higher test scores, improved course completion rates, and increased user satisfaction. These experiential gains create a "growth flywheel," wherein improved learner outcomes foster loyalty, drive word-of-mouth promotion, and enable subscription model stability—leading ultimately to expanded market reach.

Empirical cases further validate this model. EdTech platforms that employ robust LEO strategies often enjoy longer user life cycles, diversified product portfolios, and greater success in entering new educational verticals and regional markets. For example, many Chinese AI education startups have expanded beyond K-12 into lifelong learning, corporate training, and vocational skill development, propelled in part by enhanced user experiences that fuel sustainable engagement (Verma & Paul, 2025).

However, technological sophistication alone is insufficient for ensuring successful Market Expansion. Allahverdiyev (2025) emphasizes the importance of "technological soft power"—factors such as stakeholder digital literacy, user trust, teacher training, and administrative support. In many cases, the success of AI education platforms depends as much on institutional acceptance as on technical performance. Without buy-in from parents, educators, and decision-makers, even the most advanced platforms may face resistance in school environments, especially in sensitive contexts like K-12 or public higher education.

Moreover, ethical and regulatory considerations surrounding personalization are becoming increasingly complex. As personalization algorithms grow more sophisticated and intrusive, issues of data privacy, algorithmic bias, and AI explainability are moving to the forefront of academic and policy debates. Westerbeek (2025) warns that the absence of a clear regulatory framework may lead to over-reliance on opaque algorithmic processes, risking user trust and exacerbating digital inequities. The potential for misuse or unintended discrimination through data-driven decision-making demands careful attention to compliance systems, ethical design, and platform transparency, particularly during rapid market growth.

In light of these multidimensional dynamics, it is evident that Data-Driven Personalization does not operate in isolation. Its successful implementation and contribution to Market Expansion are contingent upon a range of interrelated factors—including infrastructure readiness, learning experience quality, stakeholder alignment, and ethical safeguards. These elements together form the strategic foundation upon which AI education startups can build sustainable and scalable business models.

To further understand these relationships, a growing number of researchers have turned to quantitative modeling techniques, particularly Structural Equation Modeling (SEM). Glebova, Su, and Desbordes (2025) used SEM to reveal that Learning Experience Optimization significantly mediates the causal relationship between DDP and Market Expansion. Their findings also support the hypothesis that TIR moderates the effect of personalization strategies, showing that marginal benefits increase in better-equipped regions. Such insights underscore the value of formal modeling in unpacking the causal chains and conditional pathways that define EdTech innovation success.

Driven by these theoretical advancements and practical imperatives, this study aims to develop and empirically test a comprehensive conceptual framework that captures the multifaceted dynamics of AI-powered education platforms. Specifically, the framework investigates the direct impact of Data-Driven Personalization (DDP) on Market Expansion (ME), the mediating role of Learning Experience Optimization (LEO), and the moderating influence of Technological Infrastructure Readiness (TIR). By integrating these constructs, the model provides a holistic perspective that mirrors the realities EdTech startups face—where growth is not determined by technology alone, but by the synergy of personalized learning design, experiential engagement, infrastructural capacity, and contextual regulation. In doing so, this research contributes not only to the academic discourse but also offers actionable insights for platform developers, policymakers, and digital education entrepreneurs striving to navigate a rapidly evolving innovation ecosystem.

Furthermore, the Market Expansion under consideration in this study is not confined to simple user base growth or short-term revenue gains. Rather, it reflects a multidimensional perspective on platform scalability, encompassing the diversification of educational services—such as AI-driven learning analytics for corporate training and professional certification—the evolution of partnership models, including public-private collaborations with schools, universities, and government agencies, and the broadening of user demographics, extending beyond traditional student populations to include lifelong learners, adult professionals, and educators themselves. This broader lens captures the complex nature of EdTech expansion in today's rapidly evolving, fragmented, and often inequitable digital economies, where success hinges on adaptability, inclusiveness, and ecosystem-level innovation. Such an expanded definition enables a more accurate evaluation of an AI education startup's growth potential, strategic maturity, and long-term sustainability.

Accordingly, this study sets out with the following goals:

To conceptualize and validate the role of Data-Driven Personalization in enhancing Learning Experience Optimization;

To empirically assess how LEO mediates the relationship between personalization and Market Expansion;

To test the moderating effect of Technological Infrastructure Readiness on the DDP–LEO linkage;

To contribute to the theoretical and practical understanding of growth strategies in AI-driven education startups.

Through a robust empirical analysis of AI education startups, primarily focused on China's G Province—an innovation-rich region with strong digital infrastructure—this study provides critical insights into how emerging companies can better align their personalization strategies with infrastructural realities and user experience goals. Ultimately, it seeks to reveal the internal logic and strategic pathways by which personalization evolves from a technical feature to a driver of sustainable, inclusive, and ethical market growth.

Research Objective (s)

As the EdTech industry embraces Artificial Intelligence (AI) and Big Data as core drivers of digital transformation, the deployment of Data-Driven Personalization (DDP) has become a focal strategy for education startups seeking both pedagogical and commercial success. While prior studies have examined the efficacy of personalization in improving learning outcomes (Ayodeji et al., 2024; Danylchenko-Cherniak, 2024), relatively little attention has been paid to how these personalized learning models translate into Market Expansion (ME)—a critical objective for AI education startups operating in highly competitive, technology-saturated environments (Verma & Paul, 2025).

This study addresses this research gap by articulating a set of interlinked research objectives that focus on the causal, mediating, and moderating relationships between Data-Driven Personalization, Learning Experience Optimization, Technological Infrastructure Readiness, and Market Expansion. Specifically, the research is structured around the following four objectives:

1. To investigate the impact of Data-Driven Personalization on Learning Experience Optimization in AI education platforms

The first objective is to assess how DDP affects the quality of the learner's experience across cognitive, behavioral, and emotional dimensions. Data-driven personalization enables platforms to deliver tailored content, dynamically adapt learning paths, and generate real-time feedback based on learner data (Sousa & Rocha, 2024). These systems rely on algorithms trained on user behavior data—such as clickstreams, quiz responses, and time-on-task—to optimize engagement, minimize cognitive overload, and maintain motivation (Jerebtsov & Kravets, 2025).

Previous empirical work suggests that personalized learning systems significantly enhance learner autonomy, reduce dropout rates, and improve overall satisfaction (Yang et al., 2025). Yet, the precise extent to which DDP contributes to Learning Experience Optimization (LEO) in emerging markets remains understudied, particularly when considering regional disparities in infrastructure, user literacy, and institutional support (Kapranov et al., 2025). Thus, the first objective is to empirically quantify the direct effect of DDP on LEO, offering a granular understanding of how personalization mechanisms shape the user journey.

2. To explore whether Learning Experience Optimization mediates the relationship between Data-Driven Personalization and Market Expansion

The second objective moves beyond direct effects to evaluate whether LEO serves as a mediating mechanism linking DDP to ME. From a theoretical standpoint, this objective draws on the Service-Dominant Logic (Vargo & Lusch, 2008), which posits that value is co-created through interactive experiences between users and platforms. In this context, enhanced learning experiences foster user retention, satisfaction, and referral behavior, which are key drivers of organic market expansion (Holmström, 2022).

Empirical studies have found strong correlations between learner experience quality and metrics such as Net Promoter Score (NPS), subscription renewal rates, and course repurchase (Du, 2025; Kiran & Gopal, 2025). Learning experiences are also associated with increased time-on-platform, higher average revenue per user (ARPU), and better outcomes in freemium-to-paid conversions. Hence, the second research objective is to test whether the influence of personalization on market performance is indirect and funneled through improvements in user experience—a hypothesis that, if validated, could reshape how EdTech startups allocate resources and prioritize feature development.

3. To determine the moderating role of Technological Infrastructure Readiness in the DDP–LEO pathway

Despite the promise of AI in education, infrastructure limitations—such as poor connectivity, device incompatibility, or low digital literacy—can prevent platforms from achieving their full personalization potential. The third objective is to examine whether Technological Infrastructure Readiness (TIR) moderates the effectiveness of DDP in improving the learning experience. Building on the Technology–Organization–Environment (TOE) framework (Nguyen et al., 2024), this objective posits that the same personalization strategy may yield divergent outcomes depending on the technological context.

Regions or user segments with high TIR—defined by stable networks, high-quality terminals, user support systems, and cloud AI integration—are expected to benefit more from DDP strategies (Sidani & Harb, 2025). In contrast, startups operating in low-TIR environments may encounter implementation friction, user dissatisfaction, or system underutilization. Therefore, this objective seeks to empirically test the conditional effect of TIR on the DDP–LEO linkage, providing evidence on whether personalization should be adjusted or staged based on infrastructure profiles.

4. To construct and validate a structural equation model that explains the interrelationship between DDP, LEO, TIR, and ME

The fourth objective integrates the previous goals into a comprehensive conceptual framework validated through Structural Equation Modeling (SEM). This approach enables a multivariate analysis of both direct and indirect effects, while controlling for latent variables such as user motivation, institutional policy, or platform maturity (Glebova, Su, & Desbordes, 2025). The SEM model will estimate the causal path coefficients among DDP, LEO, and ME, and test the significance of the moderating role of TIR.

By doing so, the study contributes a theoretically grounded and empirically validated model that can inform both academic inquiry and platform strategy. Startups can use this model to simulate user and market outcomes under varying degrees of personalization intensity and infrastructure readiness, while researchers can build upon the framework to examine other mediators (e.g., trust, digital literacy) or moderators (e.g., institutional governance, funding models).

In sum, these four objectives together provide a holistic roadmap for understanding the strategic utility of Data-Driven Personalization in AI-enabled education platforms. The outcomes of this investigation are expected to deliver actionable insights for EdTech entrepreneurs, digital learning designers, and policymakers seeking to foster effective and scalable AI education solutions.

Literature Review

Introduction to Thematic Foundations

As Artificial Intelligence (AI) reshapes the architecture of educational systems, the EdTech industry has witnessed an explosion of research interest around personalization, learning experiences, infrastructure, and scalability. This section systematically reviews the evolution and empirical findings of four key constructs—Data-Driven Personalization (DDP), Learning Experience Optimization (LEO), Technological Infrastructure Readiness (TIR), and Market Expansion (ME)—to synthesize theoretical underpinnings and highlight research gaps addressed in this study.

Evolution of Data-Driven Personalization in AI Education

Historical Conceptualization

DDP originates from adaptive learning systems of the 1990s, which relied on static rules to adjust content based on learner test performance (Pedrycz et al., 2024). With the advent of machine learning and big data, personalization evolved into an intelligent, data-driven process integrating learner profiles, behavioral analytics, and contextual information.

Modern Applications and Technology Stack

Since 2019, personalization has matured through AI fusion engines that combine content recommendation with predictive analytics. GPT-based generative models now enable automated assessment and dialogue-based learning, reinforcing closed-loop personalization systems (Schroth et al., 2024; Jamkhandi, 2025). These advancements mark a transition from adaptability to predictability and evolution in personalized education.

Use Cases Across Education Segments

In K-12, personalization emphasizes scaffolding through knowledge mastery modeling (Danylchenko-Cherniak, 2024);

In Higher Education, data from LMS, video logs, and discussion forums enable multimodal adaptation;

In Vocational and Lifelong Learning, real-time tutors and task-based sequencing optimize working adult engagement (von Leipzig et al., 2024);

Social and gamified data are increasingly embedded to support peer interaction and motivation (Shen et al., 2025).

Challenges and Ethical Debates

While personalization enhances learning efficiency, it also introduces challenges:

Algorithmic opacity creates fairness and interpretability concerns (Gilbert et al., 2025);

Data privacy risks emerge from behavioral and biometric tracking (Cascella, 2025);

Platform monopolization leads to resource inequality in smaller EdTech startups.

Learning Experience Optimization (LEO) as a Mediator

Conceptual Development

LEO refers to a learner-centered strategy focusing on enhancing cognitive, affective, and behavioral dimensions of engagement. Powered by AI tools such as emotion detection and real-time feedback, modern platforms can dynamically optimize the user journey (Magbilang et al., 2024).

Evaluation Metrics

LEO effectiveness is measured by:

Engagement: task completion rates and time-on-platform;

Motivation: gamification effectiveness and behavioral intention;

Interactivity: interface usability and feedback responsiveness;

Achievement: assessment improvement and learning goal alignment (Dieckmann et al., 2024).

Theoretical Alignment

From the Information Processing Theory (IPT) to Vygotsky's ZPD, personalization aligns learner challenge levels with cognitive capacity (Cao et al., 2025). The AI feedback loop contributes to higher-order thinking and metacognitive control.

Cross-Cultural and Practical Constraints

LEO implementation varies by culture. While Western models emphasize autonomy, Eastern models prioritize structure and teacher guidance (Thomas, 2024). Teachers' digital fluency also affects experience delivery (Wu & Chen, 2025). Furthermore, trust in AI personalization and the ability to interpret feedback remain critical factors (Dudnyk, 2025).

Technological Infrastructure Readiness (TIR) as a Moderator

Evolution from Hardware to Ecosystems

TIR has evolved from measuring internet penetration and device availability to include system integration, data governance, and user literacy. Modern TIR encompasses physical (network, devices), organizational (LMS compatibility), legal (GDPR adherence), and human (teacher tech adoption) layers (Kapranov et al., 2025).

Global Stratification

Countries like Finland and Singapore score high on TIR, enabling full-scale integration of AI platforms. In contrast, rural or developing regions face connectivity bottlenecks, insufficient devices, and regulatory ambiguities (Samiha & Aksara, 2025; Che'Rus et al., 2025).

Impact on DDP Effectiveness

TIR significantly moderates DDP outcomes. In high-TIR settings, personalization systems thrive and reinforce LEO outcomes. In low-TIR areas, even superior algorithms underperform due to infrastructural gaps (Knights et al., 2024).

Market Expansion (ME) in the Age of AI EdTech

Conceptual Redefinition

Originally tied to geography or revenue, ME now encompasses:

User Retention and Lifecycle: enhanced through LEO (Pinski, 2024);

Revenue Model Diversification: B2C → B2B/B2G via subscription or licensing (Serwatka, 2024);

Demographic and Cultural Reach: deploying in new markets with localization strategies (Arulnathan, 2025).

The AI Platform Flywheel

Holmström (2022) posits a feedback loop: better personalization → better experience → user growth → more data → stronger AI → better personalization. This endogenous cycle, validated through empirical studies, is now a core strategy in AI-driven market growth.

Challenges and Constraints

Despite high scalability, ME is hindered by:

Policy variability across countries (Idowu, 2025);

Cultural incompatibility in content adaptation (Malicse, 2025);

Resource asymmetry in localization and brand trust (Ghoreishi & Nielsen, 2025).

Theoretical Integration and Gaps

This review reveals an interdependent system:

DDP drives LEO (Cao et al., 2025; Tozadore et al., 2025);

LEO enhances ME through retention and satisfaction (Du, 2025);

TIR moderates both DDP and LEO's effectiveness (Sidani & Harb, 2025);

Ethical design and algorithmic transparency cut across all domains (Gilbert et al., 2025; Abbas et al., 2025).

However, few studies comprehensively model these interactions. Most treat DDP, LEO, or ME in isolation or ignore moderating infrastructure effects. This study addresses these gaps through an integrated SEM framework.

Methodology

Research Design and Rationale

This study adopts a quantitative, explanatory research design, employing structured survey data to systematically examine the impact of Data-Driven Personalization (DDP) on Market Expansion (ME), with Learning Experience Optimization (LEO) as a mediating variable and Technological Infrastructure Readiness (TIR) as a moderating factor. The research framework reflects a rigorous empirical approach, grounded in the methodological traditions of digital education research, where structural equation modeling (SEM) is commonly used to uncover the causal relationships between strategic technology adoption, user-centered design, and platform scalability. This design choice is aligned with a growing body of scholarship in the EdTech domain that emphasizes the importance of modeling interdependent system variables to explain growth trajectories and performance outcomes (Glebova, Su, & Desbordes, 2025; Nguyen et al., 2024). By adopting this approach, the study offers a robust analytical lens to test both direct and indirect effects in complex educational innovation ecosystems.

Given the interdependence of personalization strategies, experiential variables, and environmental constraints, this study employs Structural Equation Modeling (SEM) as the primary analytical technique to explore and validate the hypothesized relationships among the core constructs: Data-Driven Personalization (DDP), Learning Experience Optimization (LEO), Market Expansion (ME), and Technological Infrastructure Readiness (TIR). SEM offers several advantages for this research context. First, it allows for the simultaneous estimation of complex, multivariate relationships, including both direct and indirect effects, which is essential for understanding how LEO mediates the influence of DDP on ME. Second, SEM facilitates the testing of moderating effects, enabling the analysis of whether TIR alters the strength or direction of the DDP–LEO link. This capacity for capturing latent constructs through multiple observed indicators also helps ensure greater measurement precision and construct validity (Cao et al., 2025). Given the multifactorial nature of AI-enabled education systems—where platform design, user engagement, infrastructure, and market performance are intricately linked—SEM is uniquely well-suited to disentangle these dynamics within a single coherent statistical framework.

Measurement of Constructs and Instrumentation

Data-Driven Personalization (DDP)

DDP was operationalized based on Zhu and Yang's (2023) “Recommendation–Adaptation–Feedback” triadic model and Liu et al.’s (2024) work on AI learning platforms. Items assessed the extent to which AI systems recommend content, adjust learning paths, analyze user behavior, and generate personalized feedback. A total of 9 items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), including:

“Our platform dynamically recommends content based on user learning data.”

“The system proactively identifies knowledge gaps and pushes relevant content.”

Cronbach's Alpha for this scale was 0.91, indicating strong internal consistency.

Learning Experience Optimization (LEO)

LEO measurement was adapted from AbuKhousa et al. (2023), covering three dimensions: perceived cognitive improvement, motivational experience, and interactive system design. Items included:

"Students show stronger motivation to learn when using the platform."

"The platform's interactivity and feedback mechanisms increase user engagement."

A total of 9 items were used with a Cronbach's Alpha of 0.89, reflecting acceptable reliability.

Market Expansion (ME)

ME was defined based on Issa et al. (2022) and Holmström's (2022) AI flywheel model. Key aspects included user acquisition, retention, service diversification, and user referral:

"The number of users on our platform has continued to grow over the past 12 months."

"Word-of-mouth communication from users has become one of our main sources of growth."

Nine indicators were measured (5-point Likert), yielding a reliability coefficient of 0.92.

Technological Infrastructure Readiness (TIR)

TIR was constructed using the TOE (Technology–Organization–Environment) framework (Nguyen et al., 2024) and extended by Sidani & Harb (2025). This 9-item scale included:

"Users generally have devices that can use the platform smoothly."

"Policies and institutions positively support platform deployment."

This construct demonstrated good reliability with Cronbach's Alpha = 0.87.

Sampling and Respondent Profile

The target population for this study comprised AI education startups operating within Province G, China, a region recognized for its strong commitment to digital transformation and its strategic investment in artificial intelligence across the education sector. The selection of this geographic focus was intentional, as Province G has implemented regional policy initiatives and funding mechanisms aimed at fostering AI-driven innovation in teaching and learning. Startups in this ecosystem benefit from access to government-supported incubators, pilot program opportunities, and digital infrastructure subsidies, making it a fertile environment for examining advanced EdTech practices. These startups typically develop and deploy a wide range of AI-enhanced educational products, including adaptive learning platforms, real-time feedback systems, personalized content recommendation engines, and behavioral analytics dashboards. Their services span across K–12 education, adult literacy and upskilling programs, and vocational training, allowing them to address the learning needs of diverse demographic segments. This diversity in service offerings and market segments made Province G an ideal empirical setting to assess the impact of personalization strategies on broader market expansion outcomes within a rapidly evolving and competitive EdTech landscape.

Sampling Method

The study adopted a cluster probability sampling strategy, which allowed for a structured and representative selection of AI education startups by grouping them based on geographical location within Province G and sectoral specialization, such as K–12 education, adult learning, or vocational training. This approach ensured that the sample captured the heterogeneity of the EdTech ecosystem, accounting for differences in market maturity, product types, and user demographics. Following

Yamane’s (1973) formula for determining sample size in finite populations, with a confidence level of 95% and a margin of error of 5%, the minimum required sample size was calculated to be 258 respondents. To further enhance statistical power and reduce potential non-response bias, the researchers distributed 450 structured questionnaires to qualified respondents, including product managers, data analysts, and executives familiar with platform strategies. Ultimately, 442 valid and complete responses were obtained, resulting in a high response rate (98.2%) and ensuring robust data adequacy. This sampling outcome enhances the external validity and generalizability of the study’s findings to the broader population of AI education startups operating under similar policy and infrastructural conditions.

Demographic Composition

Gender: 53.8% male, 46.2% female

Establishment Year: 44.6% were founded post-2020, reflecting a young and tech-native cohort

Sector: 42.8% served K-12, followed by vocational/adult training (29.6%)

User Scale: 74.5% served 10,000–200,000 users

Primary Challenge: 37.1% reported “market expansion” as their top concern

Data Collection Procedures

A structured questionnaire was administered electronically and through in-person visits. Ethical standards of anonymity and informed consent were strictly followed. Respondents included founders, product managers, and data scientists familiar with platform operations and user analytics.

To ensure content validity, the survey was pre-tested with 20 EdTech professionals and revised based on their feedback. Following distribution, the data was entered into SPSS 25 and AMOS 26 for subsequent analysis.

Analytical Strategy

The study applied Structural Equation Modeling (SEM) using AMOS to test both the measurement model and the structural path model.

Descriptive and Reliability Analysis

All constructs demonstrated strong internal consistency:

DDP: $\alpha = .91$

LEO: $\alpha = .89$

ME: $\alpha = .92$

TIR: $\alpha = .87$

KMO value = 0.89; Bartlett’s Test of Sphericity was significant ($p < .001$), validating the suitability of the data for factor analysis.

Confirmatory Factor Analysis (CFA)

CFA showed acceptable model fit:

$\chi^2/df = 2.36$

RMSEA = 0.054

CFI = 0.956

TLI = 0.941

All factor loadings exceeded 0.60, and AVE values were above 0.50, confirming convergent validity.

Path Analysis and Mediation Test

SEM results revealed:

DDP significantly predicted LEO ($\beta = 0.96$, $p < .001$)

LEO significantly influenced ME ($\beta = 0.28$, $p < .001$)

DDP had a direct effect on ME ($\beta = 0.71$, $p < .001$)

Indirect effect of DDP on ME via LEO was also significant ($\beta = 0.26$), indicating partial mediation

Moderation Analysis

To examine the potential moderating effect of Technological Infrastructure Readiness (TIR) on the relationship between Data-Driven Personalization (DDP) and Learning Experience Optimization (LEO), the study followed a standard moderation analysis procedure. Specifically, mean-centering was applied to both DDP and TIR variables to reduce multicollinearity, and an interaction term (DDP × TIR) was constructed to capture any potential multiplicative effects. This interaction term was then entered into the structural model to test whether the strength or direction of the DDP–LEO relationship varied significantly across different levels of TIR. However, the analysis yielded no statistically significant path from the interaction term to LEO ($p > 0.05$), indicating that TIR did not moderate this relationship in a meaningful way within the sampled population. One likely explanation for this result is the relative infrastructure homogeneity in Province G, which already benefits from widespread broadband access, cloud service integration, and device saturation. As Knights et al. (2024) suggest, once a region surpasses a certain digital readiness threshold, infrastructural variance may become a non-differentiating factor in the perceived effectiveness of personalization strategies.

Validity and Ethical Considerations

Construct Validity

Factor loadings, composite reliability (CR > 0.7), and AVE (Average Variance Extracted > 0.5) supported the internal structure of constructs.

Common Method Bias

Harman's single factor test showed the first factor accounted for 28.6% of the variance—well below the 50% threshold—suggesting no serious common method bias.

Ethical Compliance

All participants were fully briefed on the purpose, scope, and voluntary nature of the study prior to their involvement. A detailed informed consent statement was provided at the beginning of the questionnaire, outlining the research objectives, expected time commitment, potential risks, and the right to withdraw at any time without penalty. Participants were assured that their responses would remain strictly anonymous, and no personally identifiable information was collected. To ensure compliance with both national and international data protection standards, all data were securely stored on encrypted drives with access limited to the principal investigators. The study strictly adhered to the Data Protection Law of the People's Republic of China, particularly in terms of safeguarding sensitive digital information, and was also conducted in accordance with the General Data Protection Regulation (GDPR) of the European Union, reflecting global best practices for ethical research. These measures ensured that participant privacy, autonomy, and data security were upheld throughout the entire research process, thereby enhancing the ethical integrity and credibility of the study's findings.

Results

This section presents the empirical results derived from a structured questionnaire administered to 442 respondents across AI education startups in Province G, China. The analytical process followed a structured sequence—starting with descriptive statistics and demographic insights, progressing through Confirmatory Factor Analysis (CFA), and concluding with hypothesis testing through Structural Equation Modeling (SEM). Mediation and moderation effects were also evaluated to examine the interplay among variables: Data-Driven Personalization (DDP), Learning Experience Optimization (LEO), Technological Infrastructure Readiness (TIR), and Market Expansion (ME).

Descriptive Statistics and Demographics

Among the final sample of 442 valid respondents, the gender distribution was relatively balanced, with 53.8% identifying as male and 46.2% as female, reflecting a fairly diverse representation of leadership and operational roles in the AI education startup space. Regarding organizational demographics, a significant proportion of companies—44.6%—were established in 2020 or later, highlighting the emergence of a new wave of tech-native education enterprises that have grown rapidly in the post-pandemic era, particularly in response to increased demand for remote and personalized learning solutions.

In terms of platform reach, the majority of respondents (74.5%) reported that their platforms served between 10,000 and 200,000 cumulative users, placing them in the mid-growth phase of EdTech scalability. This user base distribution suggests a high potential for operational data collection and algorithmic optimization. When asked about their primary strategic challenge, 37.1% of firms selected "market expansion", indicating that while many have achieved product–market fit, they now face pressure to expand across geographies or segments. Sector-wise, K–12 education dominated the sample (42.8%), followed by vocational and adult training (29.6%), illustrating the dual focus of AI startups on foundational learning and lifelong skill development.

Confirmatory Factor Analysis (CFA)

CFA was conducted to validate the measurement model using AMOS 26. Model fit indices met accepted thresholds:

$\chi^2/df = 2.36$ (acceptable ≤ 3),

RMSEA = 0.054 (acceptable ≤ 0.08),

CFI = 0.956 and TLI = 0.941 (both acceptable ≥ 0.90).

All factor loadings exceeded 0.60 and were statistically significant ($p < .001$). AVE values for DDP (.67), LEO (.65), ME (.69), and TIR (.61) exceeded the 0.50 benchmark, indicating strong convergent validity (Cascella, 2025). Composite reliability scores were > 0.85 across constructs, demonstrating internal consistency.

Hypothesis Testing via SEM

Path Coefficients and Direct Effects

The results confirmed three primary hypotheses:

H1: DDP significantly and positively influences LEO

$\rightarrow \beta = 0.96, t = 75.22, p < .001$

This aligns with prior research suggesting personalization enhances learners' motivation, focus, and engagement (Ayodeji et al., 2024; Cao et al., 2025).

H2: LEO significantly influences ME

$\rightarrow \beta = 0.28, t = 7.79, p < .001$

LEO operates as a value amplifier, translating learning satisfaction into business growth (Du, 2025).

H3: DDP significantly influences ME directly

$\rightarrow \beta = 0.71, t = 19.78, p < .001$

This supports the proposition that personalization itself is a strategic business engine, contributing to word-of-mouth diffusion and retention (Tozadore et al., 2025).

Mediation Analysis: LEO as Mediator

The indirect effect of DDP on ME via LEO was tested using bootstrapping (n = 5000, 95% CI):

Indirect effect = 0.2634 (CI: [0.1919, 0.3383], $p < .001$).

As the confidence interval does not include zero, the mediation is statistically significant. LEO thus partially mediates the DDP–ME relationship. This reinforces Holmström's (2022) "AI flywheel" theory: better personalization enhances experience, which in turn drives retention and referral—key mechanisms for expansion.

These results contribute to personalization theory by emphasizing the dual pathway: direct (personalization → expansion) and indirect (personalization → experience → expansion). The dual mechanism reflects a strategic need for startups to invest in both algorithmic systems and user-centric design (Jerebtsov & Kravets, 2025).

Moderation Analysis: TIR as Moderator

Moderation was tested by creating an interaction term (DDP × TIR). The regression model showed:

Interaction effect on LEO: $\beta = 0.016$, $p = .874$

Not statistically significant.

Interaction effect on ME: $\beta = 0.023$, $p = .792$

Also not significant.

These results indicate that Technological Infrastructure Readiness does not significantly moderate the effect of DDP on LEO or ME in this context. One possible reason is the relatively homogeneous infrastructure level in Province G, which already benefits from stable broadband, institutional support, and user readiness (Nguyen et al., 2024; Sidani & Harb, 2025).

Although surprising, this finding supports recent evidence that once minimum infrastructure thresholds are met, differentiating impact shifts to personalization quality and user experience design, rather than technical constraints (Gilbert et al., 2025; Kapranov et al., 2025).

Supplementary Analyses

ANOVA by Firm Characteristics

ANOVA tests were conducted across groups categorized by:

Company age (founding year),

Platform size (number of users),

Primary sector (K–12, vocational, etc.)

Results showed significant variance ($p < .001$) across all dimensions:

Older companies scored slightly lower on DDP and LEO;

Large platforms (> 200k users) had significantly higher ME and LEO scores;

K–12 and vocational sectors exhibited higher TIR and LEO scores.

These findings highlight contextual variations in construct perception and implementation, echoing prior calls for segmented platform strategies (Verma & Paul, 2025).

Correlation Matrix

Pearson correlations indicated strong inter-construct relationships:

DDP ↔ LEO: $r = .963$

DDP ↔ ME: $r = .977$

LEO ↔ ME: $r = .961$

TIR ↔ ME: $r = .834$

TIR ↔ DDP: $r = .776$

($^{**}p < .01$)

The high magnitude suggests that personalization, experience design, and infrastructure maturity are deeply interlinked in EdTech startup ecosystems.

Discussion

This study empirically explored how Data-Driven Personalization (DDP) affects Market Expansion (ME) among AI education startups in China's G Province, with Learning Experience Optimization (LEO) as a mediator and Technological Infrastructure Readiness (TIR) as a potential moderator. The findings contribute to ongoing debates in educational technology research, platform growth strategy, and human-centered AI systems.

Personalization as a Core Competency for AI Education Startups

The results reinforce the growing consensus that DDP is not merely a technical feature but a strategic foundation for platform differentiation. The positive and significant relationship between DDP and LEO confirms earlier findings that personalized learning platforms improve engagement, reduce cognitive load, and increase motivational alignment (Ayodeji et al., 2024; Jerebtsov & Kravets, 2025). In particular, respondents reported strong perceptions of personalized content recommendations, real-time learning path adjustments, and automated feedback loops.

This finding strongly validates the emerging "experience-first" paradigm in AI education platform design, which posits that the true value of algorithmic personalization lies not merely in optimizing academic outcomes, but in shaping holistic, emotionally resonant learning experiences. By dynamically adapting to individual learner needs—through real-time content recommendations, progress-based feedback, and intuitive user interfaces—AI platforms foster a sense of control, motivation, and achievement. These elements contribute directly to learner satisfaction, which has been consistently identified as a primary driver of platform stickiness, long-term engagement, and organic user growth via social sharing and referrals. In today's hyper-competitive EdTech landscape, where product features are rapidly commoditized and first-mover advantages are increasingly short-lived, it is this experience layer—enabled by personalization—that becomes the engine room of sustained and defensible growth. This is especially true in unstructured and fragmented educational markets, where learner diversity, uneven institutional support, and complex local contexts make standardized content offerings less effective. Here, the ability to deliver tailored, meaningful learning journeys becomes not only a pedagogical advantage, but a strategic necessity.

Learning Experience Optimization as a Mediating Bridge

The most profound insight of this study lies in the role of LEO as a behavioral and perceptual mediator. The significant indirect effect of DDP on ME through LEO substantiates the Service-Dominant Logic (SDL) theory (Vargo & Lusch, 2008) and the AI platform flywheel model (Holmström, 2022), which posit that user experience is central to co-created value and retention dynamics.

LEO encompasses not only functional usability but also emotional resonance—perceptions of achievement, enjoyment, and community. These elements are consistently linked to loyalty and repurchase, forming the micro-foundation of market scaling through referrals and engagement loops. This finding is aligned with recent scholarship emphasizing that the experience, not the algorithm, is the product in digital education (Malicse, 2025; Wu & Chen, 2025).

In real-world operations, this suggests that AI education firms should not rely solely on technological novelty, but focus on how personalization shapes learners' emotional and cognitive journeys—particularly in milestone moments like assessment feedback, gamified progression, and content review experiences.

Regional and Sectoral Specificity of Infrastructure Effects

Contrary to earlier research that emphasized infrastructure as a prerequisite for AI deployment (Nguyen et al., 2024), this study found no significant moderating effect of TIR on the DDP → LEO pathway. This divergence likely results from sample homogeneity—the study focused on Province G, where digital infrastructure is relatively standardized and government-backed deployments are already mature.

However, this does not discredit the value of TIR entirely. Instead, it points to a contextual saturation effect: once a certain infrastructure threshold is reached (e.g., broadband, device access, LMS compatibility), further variation becomes less influential than interface quality, content relevance, and feedback immediacy (Kapranov et al., 2025). In lower-tier regions or underserved markets, infrastructure could still be a decisive barrier.

This highlights the need for regionally stratified strategies. Startups should deploy adaptive TIR-indexed personalization rollouts, where infrastructure maturity informs the level and type of AI interventions (e.g., full-featured recommendation vs. lightweight logic routing).

Strategic and Theoretical Implications

This study advances the strategic model of "Personalization → Experience → Growth" as a closed-loop system, which startups can deploy for sustainable business development. While traditional growth models emphasize external stimuli (e.g., capital, partnerships), this endogenous model focuses on leveraging user feedback and satisfaction to stimulate internal product upgrades and social diffusion.

Moreover, by confirming partial mediation, the study highlights that DDP has both a direct marketing value (e.g., product appeal, enrollment hooks) and an indirect loyalty value (e.g., retention, subscription renewal). Hence, personalization should be treated as a dual-capacity capability: promotional and experiential.

On the theoretical front, the study extends EdTech literature by empirically validating the Technology–Experience–Business Logic linkage model. This bridges a crucial gap where previous studies treated DDP, LEO, and ME in isolation or lacked modeling rigor (Dieckmann et al., 2024; Mishra et al., 2024).

Implications for Practice

From a managerial standpoint, the findings suggest that startups should:

Invest in holistic personalization systems, not just content recommendation modules;

Integrate experience metrics (e.g., learner satisfaction, emotional engagement) into KPIs for platform performance;

Prioritize infrastructure audits when entering new markets, especially those with heterogeneous readiness;

Adopt adaptive strategies for LEO across different education segments (e.g., gamification in K-12 vs. skill tracking in vocational education).

Furthermore, the ANOVA findings suggest that companies with larger user bases exhibit stronger DDP, ME, and TIR scores. This implies a compounding effect: growth not only results from better personalization but also enables deeper personalization through richer data, thus creating a feedback loop for maturity and differentiation.

Limitations and Directions for Future Research

This study's scope was limited to startups in Province G, which may not reflect conditions in underdeveloped or international markets. The self-report nature of survey data may also introduce social desirability bias.

Future research should:

Conduct cross-regional comparative studies to capture variance in TIR influence;

Integrate multi-source data, such as platform log data, user reviews, and A/B test results;

Explore additional moderators, such as digital literacy or regulatory environment;

Apply longitudinal models to examine how personalization-LEO-ME dynamics evolve over time (Glebova et al., 2025; Edwards et al., 2025).

Conclusion

Summary of Key Findings

This study investigated the relationship between Data-Driven Personalization (DDP) and Market Expansion (ME) among AI education startups, with Learning Experience Optimization (LEO) serving as a mediating variable and Technological Infrastructure Readiness (TIR) as a potential moderator. Empirical results based on 442 responses and structural equation modeling revealed three main findings:

First, DDP significantly improves LEO. Adaptive algorithms, feedback mechanisms, and personalized content delivery contribute to learners' satisfaction and engagement, validating prior findings (Ayodeji et al., 2024; Zhu & Yang, 2023).

Second, LEO significantly promotes ME. A high-quality, emotionally engaging learning experience not only improves retention and loyalty but also drives user-led expansion, aligning with the Service-Dominant Logic theory (Vargo & Lusch, 2008).

Third, LEO plays a partial mediating role, meaning DDP contributes both directly and indirectly to ME. However, TIR did not significantly moderate the DDP–LEO relationship in this regional context.

These findings consolidate the theoretical path of "Personalization → Experience → Growth," offering new insight into how AI educational platforms can scale effectively through internal product innovation and experience-centered design.

Theoretical Contributions

This study advances EdTech research in several dimensions:

Personalization as a Strategic Growth Enabler

Contrary to traditional models where personalization was considered a pedagogical feature, this study confirms its strategic value for enterprise growth. Personalization not only enhances academic results but also serves as a differentiating asset in saturated EdTech markets.

LEO as an Experience-Mediated Growth Channel

By proving the mediating effect of LEO, the study validates and extends Holmström's (2022) AI flywheel model, which theorizes that user satisfaction and engagement accelerate data accumulation and system improvement, generating a self-reinforcing loop of innovation and growth.

Boundary Conditions of Infrastructure

Although TIR did not moderate outcomes significantly in this study, it remains theoretically essential. In regions with poor connectivity, insufficient device access, or low digital literacy, personalization benefits may be severely limited. This supports a context-sensitive deployment model of AI in education.

Practical Implications

For AI Education Startups

Startups should treat DDP as a core engine of growth rather than a peripheral product enhancement. This requires:

Building robust data ecosystems;

Investing in feedback-driven design;

Integrating emotional and motivational dimensions into platform architecture.

They should also shift from content-centered models to experience-first strategies, where design, UI, emotional engagement, and community interaction are seen as integral to product-market fit.

For Platform and Curriculum Designers

Curriculum design should adopt modular, personalized sequencing, driven by behavioral analytics. Emotional engagement, cognitive challenge, and motivation mechanisms (e.g., gamification, adaptive assessments) must be systematically embedded.

For Policy and Regional Governance

This study suggests a "regional digital ecology" for AI education, advocating:

Procurement pipelines for high-quality AI EdTech platforms;

Algorithmic transparency and data regulation frameworks;

Tripartite partnerships among schools, startups, and governments to ensure ethical and scalable deployment (Wang & Chen, 2024).

Limitations

Several limitations must be acknowledged:

Geographic concentration: The study focuses on Province G, a high-infrastructure region. Results may not generalize to rural or low-TIR settings.

Self-reporting bias: Despite validated scales, user perceptions may not perfectly reflect system behavior.

Cross-sectional design: Lacks time-series validation of how experiences evolve and affect growth over time.

Future Research Directions

To expand upon this study's foundation, future research can explore:

Cross-Regional Comparative Studies

Comparing platforms across provinces, regions, or countries will help identify how localization, infrastructure, and digital literacy influence the DDP–LEO–ME path (Nguyen et al., 2024).

Multi-Source Data Fusion

By integrating backend logs, interviews, and real user behavior data, scholars can construct richer models of perception–behavior–performance loops and reduce reliance on subjective assessments.

Longitudinal and Dynamic Modeling

Learning behavior evolves over time. Longitudinal analysis and A/B testing can track how platform iterations impact the DDP–LEO–ME cycle and assess retention trajectory, churn predictors, or personalization effectiveness over different user stages (Yang et al., 2025).

Psychological and Contextual Variable Integration

Variables like motivation, emotional response, digital confidence, and instructor presence could offer additional explanatory power when modeling how learners react to personalization and how experiences shape platform growth (Kapranov et al., 2025).

Concluding Thoughts

The core contribution of this study is to reconceptualize Market Expansion not as a purely commercial goal, but as a product of educational quality, experience resonance, and platform trust. In the AI era, where technological capability is widely accessible, it is the design of personalization, depth of experience, and ethical implementation that determine competitive advantage.

In summary, this study validates a holistic and empirically supported logic of "Data-Driven Personalization → Learning Experience Optimization → Market Expansion", providing:

A theoretical framework for future AI-EdTech research;

A strategic model for startup development;

A policy direction for ethical, inclusive and scalable AI education ecosystems.

As AI continues to disrupt and transform learning globally, the lessons from this study offer timely guidance on how experience, not just algorithms, will shape the future of educational equity and enterprise growth.

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