IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 27, Issue 6. Ser. 15 (June 2025), PP 08-16
www.iosrjournals.org

"Readiness of AI driven marketing strategies of educational institutions in Bangalore" - A Theory of planned behavior and Resource based view Approach

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Abstract: *The advent of artificial intelligence (AI) is revolutionizing marketing practices across various industries, including education. This study examines the readiness of educational institutions in Bangalore to adopt AI-driven marketing strategies. With increasing competition among institutions for student enrollment, the role of intelligent technologies in enhancing outreach, personalization, and operational efficiency has gained prominence. The research aims to evaluate the level of awareness, implementation, and preparedness among educational administrators to integrate AI tools in marketing functions such as lead generation, campaign automation, and student engagement. Using a structured survey administered to marketing heads and institutional managers, the study captures insights into current AI adoption levels, infrastructural challenges, strategic intent, and human capital preparedness. The findings indicate that while awareness of AI benefits is relatively high, actual implementation remains limited due to cost constraints, lack of skilled professionals, and ambiguity in strategic planning. However, institutions that have begun incorporating AI reported improved targeting and measurable return on investment. The study concludes with recommendations for capacity building, vendor partnerships, and policy-level support to accelerate AI integration in educational marketing. This research contributes to understanding the digital transformation trajectory within the educational sector and highlights the growing need for strategic AI alignment in marketing domains.*
Key Word*: AI driven marketing strategies, educational institutions, theory integration, TPB, Resource based view.*

Date of Submission: 13-06-2025 Date of Acceptance: 27-06-2025

I. Introduction

In today's digital era, Artificial Intelligence (AI) is not merely an emerging trend but a transformative force reshaping the core of various industries, with education being one of its most significant frontiers. As educational institutions strive to remain relevant, competitive, and student-focused, the impetus to adopt AI-driven marketing strategies is becoming increasingly urgent. This transformation is especially critical in urban innovation hubs like Bangalore—India's Silicon Valley—where the convergence of academia, technology, and entrepreneurial ecosystems accelerates the pressure to innovate. Within this context, AI emerges not just as a tool but as a strategic enabler capable of revolutionizing how institutions engage, recruit, and retain students. The application of AI in educational marketing spans a wide spectrum of capabilities: from predictive analytics that forecast enrollment trends to intelligent customer relationship management (CRM) systems that deliver personalized outreach. AI-powered chatbots, machine learning-based content targeting, and automated communication platforms are increasingly redefining student experiences. These innovations promise scalability, cost-efficiency, and enhanced decision-making—attributes critical to thriving in a competitive educational landscape. Despite these advantages, however, many institutions remain inadequately prepared for the adoption of AI technologies. The underlying causes are multifaceted, including technological unfamiliarity, organizational inertia, budgetary constraints, ethical apprehensions, and a lack of digitally skilled human capital.

A close look at the educational ecosystem in Bangalore reveals a fragmented digital maturity spectrum. While elite institutions such as the Indian Institute of Science (IISc) and Indian Institute of Management Bangalore (IIMB) lead with AI-enhanced platforms and data-driven strategies, a large number of mid-tier and smaller colleges continue to rely on outdated marketing approaches such as SMS blasts, print advertisements, and physical college fairs. This digital divide reflects a broader issue: AI readiness in educational marketing is not merely a matter of technology adoption but one of strategic alignment, institutional culture, and resource capability. To explore and address this disparity, the current study employs an integrative theoretical framework that combines the Theory of Planned Behavior (TPB) and the Resource-Based View (RBV). TPB, proposed by

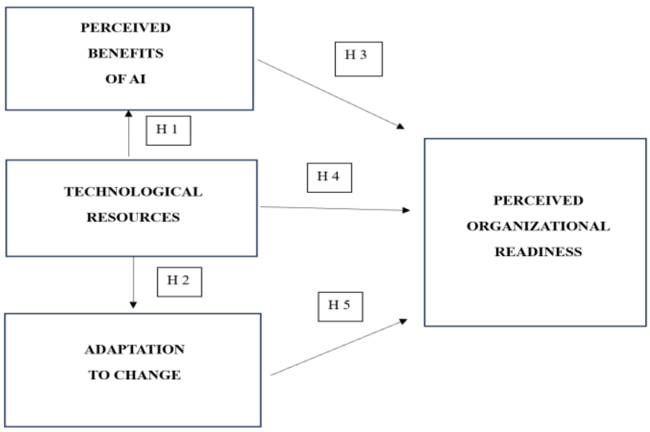
Ajzen (1991), provides a behavioral lens to examine the psychological and social dimensions of institutional decision-making—focusing on attitudes, subjective norms, and perceived behavioral control. It helps understand why institutions may support or resist AI adoption based on internal belief systems and external pressures. In contrast, RBV (Barney, 1991; Wernerfelt, 1984) offers a strategic perspective by emphasizing the role of valuable, rare, inimitable, and non-substitutable (VRIN) resources in achieving competitive advantage. This includes AI infrastructure, data literacy, and the presence of a digitally capable workforce. While TPB sheds light on intent, RBV uncovers capability. Their integration forms a comprehensive lens to assess AI readiness in a nuanced, multi-dimensional manner. The Indian educational context, particularly in Bangalore, presents an ideal landscape for this dual-lens analysis. Institutions operate under regulatory oversight and constrained resources while competing in an increasingly digital education marketplace. By bridging behavioral and strategic theories, this study aims to fill critical gaps in current literature and provide actionable insights for administrators, EdTech firms, and policymakers striving for digital transformation in education.
With context to the above the aim of the study revolves around the following objectives
1.To investigate how Theory of planned Behavior and Resources Based View can be integrated to understand the relevance of AI in marketing strategies
2.To assess how Perceived Organizational Readiness is impacted by Perceived Behavior of AI, Technological Readiness and Adaptation to Change
3.To check relevance of AI driven marketing strategies in attaining organizational objectives of educational institutions

II. Literature Review

Computer-assisted language learning (CALL) environments have demonstrated potential in providing engaging and learner-centered experiences. Platforms such as Duolingo, Quizlet, Kahoot! and WhatsApp have been instrumental in enabling vocabulary retention, real-time feedback, and increased learner motivation through gamification strategies. As Lee and Drajati (2019) assert, the application of mobile-assisted language learning (MALL) significantly enhances students' engagement and vocabulary knowledge when coupled with regular formative assessment and feedback loops. The adoption of digital storytelling, particularly collaborative platforms where learners construct narratives together, is gaining traction for its dual benefit of enhancing linguistic competence and cultural awareness (Yang & Wu, 2012). Moreover, interactive simulations and games reduce affective filters such as anxiety, thus fostering better communication and higher motivation (Zhang & Zou, 2020). Understanding the mechanisms behind the adoption of digital technologies in language learning requires a dual-theoretical approach. The Theory of Planned Behavior (TPB) explains individual behavioral intentions in terms of Attitude, Subjective Norm, and Perceived Behavioral Control. In language learning, positive teacher attitudes toward technology, peer influence, and individual confidence significantly impact the integration of digital tools (Ajzen, 1991). For instance, studies in Indonesian classrooms demonstrated that positive peer interactions through WhatsApp fostered learner autonomy and participation (Wahyuni et al., 2021). Complementing TPB, the Resource-Based View (RBV) emphasizes institutional readiness through valuable, rare, inimitable, and non-substitutable (VRIN) resources. Robust infrastructure, trained educators, and supportive policies are all essential for sustained digital adoption (Barney, 1991; Tondeur et al., 2017). A school's capacity to leverage technological tools depends not just on access, but also on how well these tools are embedded in pedagogical practices.

Digital integration has led to a shift toward constructivist and communicative models in language teaching. Teachers are evolving into facilitators and co-learners, supporting student autonomy through blended and flipped classroom models (Vygotsky, 1978; Zhang, 2019). Learners access instructional content outside of class and engage in active language use during in-person sessions. Mobile learning applications support metacognitive skills such as goal-setting, time logging, and progress tracking—key components of learner autonomy (Kukulska-Hulme, 2009). Research by Burston (2015) indicates that students using self-paced apps showed higher retention of vocabulary compared to those in traditional classroom settings. Language acquisition is not solely a cognitive process but is heavily influenced by affective and psychological factors. Working memory has been found to correlate strongly with proficiency in L2 listening and reading comprehension (Miyake & Friedman, 1998). Instructional design should therefore reduce cognitive load by presenting input in manageable "chunks" and incorporating scaffolded tasks (Sweller, 1994). The Foreign Language Classroom Anxiety Scale (FLCAS) is widely used to measure language anxiety. Technology-mediated environments often reduce anxiety levels, creating more conducive spaces for communication (Horwitz et al., 1986). For example, game-based learning and language simulations encourage communication by lowering the stakes of language production and promoting exploratory learning. Despite the promise of digital tools, the digital divide remains a pressing concern. Learners in under-resourced contexts often lack access to personal digital devices and consistent internet, limiting their participation in MALL activities (UNESCO, 2020). Gender dynamics exacerbate this divide; in some contexts, female learners have less access to personal technology, though studies show they exhibit higher collaborative engagement when provided with equal access (Oxford & Burry-Stock, 1995). Efforts to mitigate these disparities include the integration of inclusive access policies, and equity-focused digital interventions. Customization of content to reflect local cultures and languages further improves learner engagement, as it aligns better with students lived experiences (Canagarajah, 2005). One of the most significant challenges to effective digital integration is the lack of adequate teacher training. Research across various contexts, including Thailand and Turkey, has shown that while many educators are enthusiastic about using technology, they often lack the skills and confidence to do so effectively (Pimpa & Moore, 2020; Aydin, 2013). Therefore, ongoing professional development, guided mentorship, and institutional support are essential. The Resource-Based View reinforces the importance of not only having infrastructure but also investing in human capital. Teacher readiness—both in terms of digital literacy and pedagogical understanding—is crucial for meaningful technology integration. Schools with clearly defined e-learning policies and dedicated ICT units tend to exhibit more coherent and sustained implementation (Ertmer, 1999). The shift toward technology-mediated learning has necessitated rethinking assessment practices. Traditional tests, especially multiple-choice formats, may not adequately reflect learners' language competence. Instead, authentic assessments such as e-portfolios, peer-reviewed presentations, and reflective journals are increasingly adopted to provide a more comprehensive evaluation (Chun, 2006). Learning Management Systems (LMS) such as Google Classroom and Edmodo facilitate continuous assessment by tracking student progress in real time. However, concerns persist around academic dishonesty, assessment overload, and technical glitches. These underscore the need for thoughtfully designed digital assessments that balance rigor, fairness, and flexibility.

III. Model



Hypotheses

H1: Technological resources have positive impact on Perceived Benefits of AI in educational institutions of Bangalore

H2: Technological resources significantly influence adaptation to change

H3: Perceived Benefits of AI positively influences Perceived Organizational Readiness

H4: Technological resources impact positively on Perceived Organizational Readiness

H5: Adaptation to change significantly impacts Perceived Organizational Readiness

Research Methodology

Using SPSS software and a quantitative research methodology is justified for this study as it allows for empirical measurement and statistical analysis of constructs like Perceived Benefits of AI (PBA), Adaptation to Change (ACA), Technological Readiness (TRA), and Perceived Organizational Readiness (PORA). Quantitative methods are essential for validating theoretical relationships posited by the Theory of Planned Behavior (TPB) and the Resource-Based View (RBV) through objective data (Creswell, 2014). SPSS enables the use of regression, correlation, and reliability tests to analyze large datasets and identify predictive patterns, ensuring replicability and generalizability of findings (Pallant, 2020).

Sample Size

Convenience sampling is justified in this study due to the practical challenges of accessing a diverse population of stakeholders within educational institutions in Bangalore. Given the exploratory nature of AI readiness in a specific regional and institutional context, reaching available and willing participants—such as administrative staff, faculty, or IT personnel—helps collect relevant insights efficiently (Etikan, Musa, &

Alkassim, 2016). With a sample size of 265, the study gains sufficient statistical power to detect meaningful patterns, supporting generalizability within the target demographic. Convenience sampling is especially useful in early-stage research where time, accessibility, and cost constraints exist (Creswell, 2014).

IV. Analysis

Descriptive Statistics

Table no1:

	N	Minimum	Maximum	Mean	Std. Deviation
PBA	265	1.0000	5.0000	3.992453	1.0764435
ACA	265	1.0000	5.0000	3.487547	.9347843
PORA	265	1.0000	5.0000	2.870943	1.0259258
TRA	265	1.0000	5.0000	2.928302	1.0616556
Valid N (listwise)	265				

Reliability Analysis

Table no2 :

Cronbach's Alpha	N of Items
.747	4

The reliability statistics indicate that the scale used to measure the variables (PBA, ACA, PORA, and TRA) has a Cronbach's Alpha of 0.747, which suggests acceptable internal consistency. A Cronbach's Alpha value above 0.70 is generally considered satisfactory for social science research, indicating that the items in the scale reliably measure the same underlying construct. With 4 items in the scale, the results demonstrate that the measures for Perceived Benefits of AI, Adaptation to Change, Perceived Organizational Readiness, and Technological Readiness are sufficiently reliable for use in the analysis.The item statistics table presents the mean and standard deviation for each of the four variables: Perceived Benefits of AI (PBA), Adaptation to Change (ACA), Perceived Organizational Readiness (PORA), and Technological Readiness (TRA). The mean for PBA is the highest (M = 3.99, SD = 1.08), indicating a generally positive perception of AI benefits. ACA has a moderately high mean (M = 3.49, SD = 0.93), suggesting that participants are relatively adaptable to change. In contrast, both PORA (M = 2.87, SD = 1.03) and TRA (M = 2.93, SD = 1.06) have lower means, indicating perceptions of limited organizational and technological readiness for AI implementation. These results highlight areas where organizations may need to focus on improving readiness to enhance AI adoption.

Table no4: ANOVA with Tukey's Test for Non-additivity

<table>
<tr><td colspan="3"></td><td>Sum of Squares</td><td>df</td><td>Mean Square</td><td>F</td><td>Sig</td></tr>
<tr><td colspan="3">Between People</td><td>631.774</td><td>264</td><td>2.393</td><td></td><td></td></tr>
<tr><td rowspan="5">Within People</td><td colspan="2">Between Items</td><td>221.366</td><td>3</td><td>73.789</td><td>121.690</td><td>.000</td></tr>
<tr><td rowspan="3">Residual</td><td>Non-additivity</td><td>5.035[a]</td><td>1</td><td>5.035</td><td>8.382</td><td>.004</td></tr>
<tr><td>Balance</td><td>475.208</td><td>791</td><td>.601</td><td></td><td></td></tr>
<tr><td>Total</td><td>480.244</td><td>792</td><td>.606</td><td></td><td></td></tr>
<tr><td>Total</td><td>701.610</td><td>795</td><td>.883</td><td></td><td></td><td></td></tr>
<tr><td colspan="3">Total</td><td>1333.384</td><td>1059</td><td>1.259</td><td></td><td></td></tr>
<tr><td colspan="8">Grand Mean = 3.319811</td></tr>
</table>

a. Tukey's estimate of power to which observations must be raised to achieve additivity = 1.649.

The ANOVA with Tukey's test for non-additivity assesses whether there are any nonadditive effects among the variables (PBA, ACA, PORA, and TRA). The results show significant findings for both Between Items (F = 121.690, p < .001) and Non-additivity (F = 8.382, p = .004). This indicates that there is a significant nonadditive effect, meaning that the relationships between the variables do not fully meet the assumption of additivity (where the sum of effects of individual variables equals the combined effect). The residual sum of squares for non-additivity is 5.035, reflecting the variation attributed to this nonadditive effect. The Tukey's estimate of power (1.649) suggests the level of power needed to achieve additivity in the data, highlighting the degree to which the data deviates from the expected additive model. Overall, these results suggest that the interactions between the variables are not entirely additive, warranting further exploration of the underlying relationships

Correlation

Table no5:

Pearson Correlation	PBA	ACA	PORA	TRA
PBA	1	.595**	.149*	.076
ACA	.595**	1	.520**	.477**
PORA	.149*	.520**	1	.788**
TRA	.076	.477**	.788**	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The correlation matrix illustrates the relationships among the key variables in the study: Perceived Benefits of AI (PBA), Adaptation to Change (ACA), Perceived Organizational Readiness (PORA), and Technological Readiness (TRA). Pearson correlation coefficients were calculated to determine the strength and direction of the linear relationships between these variables.

PBA demonstrated a moderate positive correlation with ACA ($r = .595, p < .01$), suggesting that individuals who are more adaptable to change tend to perceive greater benefits from AI adoption. Additionally, PBA showed a weak but significant positive correlation with PORA ($r = .149, p < .05$), indicating that perceived organizational readiness may slightly influence how beneficial AI is perceived. However, the relationship between PBA and TRA was non-significant ($r = .076$), implying little to no direct association between perceived benefits and technological readiness.

ACA exhibited moderate to strong positive correlations with both PORA ($r = .520, p < .01$) and TRA ($r = .477, p < .01$), highlighting that adaptable individuals are more likely to perceive their organizations and technological systems as ready for AI implementation. A particularly strong positive correlation was found between PORA and TRA ($r = .788, p < .01$), indicating that perceived organizational readiness is closely linked with the existing technological infrastructure. These findings suggest interconnectedness between individual and organizational factors influencing AI readiness.

Regression

Table no 6 : testing for Hypothesis 3, 4, and 5

Variables Entered	Variables Removed	Method
TRA, PBA, ACA[b]	.	Enter

a. *Dependent Variable: PORA*
b. *All requested variables entered*

The table outlines the variables included in the regression model predicting Perceived Organizational Readiness (PORA). The independent variables entered were Technological Readiness (TRA), Perceived Benefits of AI (PBA), and Adaptation to Change (ACA), using the standard enter method. No variables were removed from the model, indicating that all specified predictors were retained for analysis. This setup allows for examining the combined and individual effects of technological, perceptual, and behavioral factors on perceived organizational readiness for AI implementation.

Table no7:

R	R Square	Adjusted R Square	Std. Error of the Estimate
.805[a]	.648	.644	.6124446

a. Predictors: (Constant), TRA, PBA, ACA

The model summary indicates a strong relationship between the predictors—Technological Readiness (TRA), Perceived Benefits of AI (PBA), and Adaptation to Change (ACA)—and the dependent variable, Perceived Organizational Readiness (PORA), with an R value of 0.805. The R Square value of 0.648 suggests that approximately 64.8% of the variance in PORA can be explained by the three predictors. The Adjusted R

Square (0.644) confirms the model's robustness while accounting for the number of predictors. The standard error of the estimate (0.612) reflects the average deviation of observed values from the regression line.

Table no 8:

	Sum of Squares	df	Mean Square	F	Sig.
Regression	179.968	3	59.989	159.934	.000[b]
Residual	97.898	261	.375		
Total	277.866	264			

a. Dependent Variable: PORA
b. Predictors: (Constant), TRA, PBA, ACA

The ANOVA results indicate that the regression model significantly predicts Perceived Organizational Readiness (PORA), $F(3, 261) = 159.934$, $p < .001$. The model explains a significant portion of the variance in PORA, as evidenced by the high F-value and a significance level well below the .05 threshold. The regression sum of squares (179.968) is substantially greater than the residual sum of squares (97.898), further supporting the model's effectiveness. These findings confirm that Technological Readiness (TRA), Perceived Benefits of AI (PBA), and Adaptation to Change (ACA) are significant predictors of organizational readiness.

Table no 9: Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations		
	B	Std. Error	Beta			Zero-order	Partial	Part
(Constant)	.225	.174		1.294	.197			
PBA	-.025	.046	-.026	-.538	.591	.149	-.033	-.020
ACA	.226	.060	.206	3.788	.000	.520	.228	.139
TRA	.668	.042	.692	15.811	.000	.788	.699	.581

a. Dependent Variable: PORA

The coefficients table reveals the individual contributions of each predictor to Perceived Organizational Readiness (PORA). Technological Readiness (TRA) emerged as the strongest predictor ($\beta = .692$, $p < .001$), indicating a substantial positive influence. Adaptation to Change (ACA) also significantly predicted PORA ($\beta = .206$, $p < .001$), though to a lesser extent. In contrast, Perceived Benefits of AI (PBA) did not significantly contribute to the model ($\beta = -.026$, $p = .591$). These results suggest that organizational and individual readiness factors, rather than perceived benefits, play a more critical role in shaping perceptions of AI readiness.

Table no 10: testing for Hypothesis

Variables Entered	Variables Removed	Method
TRA[b]	.	Enter

a. Dependent Variable: PBA.

Table no 11: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.076[a]	.006	.002	1.0753669	.006	1.529	1	263	.217

a. Predictors: (Constant), TRA

Table no 12: ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.768	1	1.768	1.529	.217[b]
Residual	304.137	263	1.156		
Total	305.905	264			

a. Dependent Variable: PBA
b. Predictors: (Constant), TRA

Table no 13: Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.767	.194		19.402	.000
TRA	.077	.062	.076	1.236	.217

a. Dependent Variable: PBA

The regression coefficients table indicates that Technological Readiness (TRA) is not a significant predictor of Perceived Benefits of AI (PBA). The unstandardized coefficient (B = 0.077, p = .217) suggests a positive but weak and statistically insignificant relationship. This means that for every one-unit increase in TRA, the PBA increases by 0.077 units, holding other factors constant. However, the p-value above 0.05 indicates that this relationship is not statistically meaningful. The standardized coefficient (β = 0.076) further confirms the minimal impact of TRA on PBA. Overall, the analysis suggests that technological readiness alone does not significantly influence the perceived benefits of AI.

Table no 14: for Hypothesis 2

Variables Entered	Variables Removed	Method
TRA[b]	.	Enter

a. Dependent Variable: ACA.
b. All requested variables entered.

Table no 15: Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.477[a]	.228	.225	.8231259	.228	77.482	1	263	.000

a. Predictors: (Constant), TRA

Table no 16: ANOVA[a]

	Sum of Squares	df	Mean Square	F	Sig.
Regression	52.497	1	52.497	77.482	.000[b]
Residual	178.192	263	.678		
Total	230.689	264			

a. Dependent Variable: ACA
b. Predictors: (Constant), TRA

Table no 17: Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.258	.149		15.192	.000
TRA	.420	.048	.477	8.802	.000

The regression analysis indicates that Technological Readiness (TRA) significantly predicts Adaptability to Change (ACA). The model explains 22.8% of the variance in ACA ($R^2 = .228$, $p < .001$), suggesting a moderate effect size. The unstandardized coefficient (B = 0.420, p = .000) shows that for every one-unit increase in TRA, ACA increases by 0.420 units, indicating a strong positive relationship. The standardized coefficient (β = .477) confirms that TRA is a substantial predictor of adaptability. The model is statistically significant ($F = 77.482$, $p < .001$), demonstrating that higher technological readiness is associated with greater adaptability to change among respondents.

Table no 18: Demographics of the primary data collection

Particulars		Frequency	Percent
Age	25 and below	141	53.2%
	25-35	24	9.1%
	36-45	20	7.5%
	45 and above	80	30.2%
	Total	265	100.0%
Gender	Female	114	43.0%
	Male	151	57.0%
	Total	265	100.0%

V. Discussion

This study provides critical insights into the readiness of educational institutions in Bangalore to adopt AI-driven marketing strategies, grounded in the integration of the Theory of Planned Behavior (TPB) and the Resource-Based View (RBV). It evaluates four constructs—Perceived Benefits of AI (PBA), Adaptation to Change (ACA), Perceived Organizational Readiness (PORA), and Technological Readiness (TRA)—offering a comprehensive view of how psychological and infrastructural elements influence AI readiness. Descriptive statistics reveal that while PBA scored the highest mean ($M = 3.99$), indicating strong optimism toward AI, it did not significantly predict PORA ($\beta = -.026$, $p = .591$). This finding challenges the assumption that perceived benefit alone can drive institutional change, underscoring the gap between positive perception and actionable readiness. In contrast, TRA emerged as the most powerful predictor of PORA ($\beta = .692$, $p < .001$), validating the RBV's proposition that valuable, well-managed resources—particularly technological infrastructure—are central to strategic preparedness. ACA also played a significant role ($\beta = .206$, $p < .001$), affirming TPB's assertion that behavioral intent and adaptability are essential drivers of organizational transformation. The strong correlation between TRA and PORA ($r = .788$) demonstrates a close link between infrastructure and organizational preparedness. Further, the significant relationship between TRA and ACA ($\beta = .477$, $p < .001$) suggests that technological capability enhances adaptability among individuals, a valuable insight for institutional development.

VI. Implication

Implications for Theory

This study advances the integration of the Theory of Planned Behavior (TPB) and the Resource-Based View (RBV) by demonstrating how behavioral and resource-based factors interact to influence AI readiness in educational institutions. The strong impact of Technological Readiness (TRA) on Perceived Organizational Readiness (PORA) affirms RBV's emphasis on strategic internal resources as enablers of transformation. Meanwhile, the significant role of Adaptation to Change (ACA) in predicting PORA supports TPB's claim that behavioral intention and perceived control are essential in shaping organizational outcomes. Interestingly, Perceived Benefits of AI (PBA), although high in perception, did not significantly affect PORA, challenging TPB's assumption that attitude alone drives behavior. These results highlight that readiness for AI is not purely perceptual but deeply rooted in the alignment between infrastructure and adaptability. The findings suggest a refined theoretical framework where technological assets and behavioral agility co-evolve as core components for institutional innovation in digital strategy.

Implications for Practice

The study provides practical insights for educational institutions in Bangalore aiming to implement AI-driven marketing strategies. Although Perceived Benefits of AI (PBA) are rated highly ($M = 3.99$), they do not significantly influence Perceived Organizational Readiness (PORA). This suggests that optimism toward AI must be supported by structural and human resource readiness. Institutions should prioritize Technological Readiness (TRA), the strongest predictor of PORA ($\beta = .692$, $p < .001$), by investing in IT infrastructure, scalable platforms, and technical support systems. Additionally, fostering Adaptation to Change (ACA) through continuous professional development and change management initiatives is essential, as it significantly impacts PORA ($\beta = .206$, $p < .001$). Rather than relying solely on perceived advantages, decision-makers must enhance both digital infrastructure and staff adaptability to ensure successful AI integration. These findings serve as a strategic guide for aligning internal capabilities with emerging AI-based innovations in educational marketing.

The findings offer key practical insights for educational institutions in Bangalore aiming to implement AI-driven marketing strategies. Although stakeholders perceive strong benefits of AI (PBA), this perception alone does not translate into organizational readiness (PORA). Institutions should prioritize enhancing technological readiness (TRA), which emerged as the most influential factor in building readiness. This involves investing in robust IT infrastructure, upskilling staff, and ensuring seamless digital integration. Additionally, fostering a culture that encourages adaptation to change (ACA) is critical, as it significantly contributes to organizational preparedness. Training programs, leadership engagement, and change management strategies can strengthen individuals' adaptability. Importantly, decision-makers should not rely solely on perceived advantages of AI but must align technological and human resource development efforts to achieve effective AI integration. These insights provide a strategic roadmap for educational leaders seeking to align internal capacities with technological innovation in marketing functions.

Limitations

This study, while offering valuable insights, is subject to certain limitations. Firstly, it relied on convenience sampling within Bangalore, which may limit the generalizability of findings to other regions or institutional types. Secondly, the research employed a quantitative cross-sectional design, capturing perceptions at a single point in time, thus missing potential longitudinal changes in AI readiness. Additionally, while the study examined perceptions of readiness, it did not measure actual AI implementation outcomes. Lastly, the statistical insignificance of PBA suggests that other unmeasured variables—such as leadership support or policy alignment—may influence organizational readiness more deeply.

Acknowledgement
The authors hereby declare that there is no funding sought either internal or external in completing this research paper and also take pride to thank their mentors in completing their rigorous yet relevant study.

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