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Research Article

Measuring the Impact of the National Education Policy 2020 on Public Engagement with Experiential Learning in India: An Interrupted Time Series Study (2015–2024)

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Abstract

India's National Education Policy (NEP) 2020 marked a significant pedagogical shift towards learner-centered and experiential approaches. This study investigates the policy's macro-level impact by quantifying changes in public interest in experiential learning, utilizing Google Trends data from 2015 to 2024. While existing research primarily addresses NEP's institutional and curricular dimensions, this study fills a gap by providing a long-term, data-driven analysis of its societal reception. Drawing on Information Seeking Behavior Theory, online search patterns serve as a proxy for evolving public engagement with experiential learning concepts. Grounded in Kolb's Experiential Learning Theory, eight search terms, categorized into "core ELT concepts" and "ELT-aligned pedagogical models," were selected. Interrupted Time Series (ITS) analysis was applied to assess structural shifts in search behavior post-2020 policy intervention. Results: Findings reveal a statistically significant increase in public engagement across both categories, indicating experiential learning's growing cultural traction after the NEP's announcement. This research offers a unique data-driven perspective on the reception of experiential learning in India and highlights avenues for future inquiry into education policy and public discourse.

I. INTRODUCTION

The Indian education landscape has seen significant changes in recent years. This is being driven by several factors including policy reforms (Yenugu, 2022), digital learning (Gavinolla *et al.,* 2021), artificial intelligence (AI) and big data (Bhutoria, 2022), and focus on equity and inclusion (Mukhopadhyay & Sriprakash, 2019). There has been a gradual shift away from traditional assembly-style rote learning methods toward more interactive and experiential approaches. Increasingly, the learner is at the center of the educational process, shaping the development of new pedagogies. This transformation has been significantly shaped by the National Education Policy (NEP) 2020, a landmark reform that reimagines Indian education in line with 21st-century needs (Raj, 2025).

Among its many aspects, NEP 2020 places strong emphasis on experiential learning models. The policy calls for pedagogy that is “more experiential, holistic, integrated, inquiry-driven, discovery-oriented, learner-centered, discussion-based, flexible, and enjoyable” (MHRD, 2020, p.3). It encourages the use of project-based tasks, real-world case studies, hands-on activities, and reflective practices to foster deeper understanding of any subject. They are intended to spark curiosity among learners, sharpen thoughts, and anchor knowledge in lived experiences—skills essential for a knowledge-driven society.

NEP 2020 has generated wide-ranging academic research—spanning teacher training, multilingualism, curriculum restructuring, inclusive education, and equitable access (Beerannavar & Pancrasius, 2024; Rangarajan et al., 2025; Singh, 2025). Yet, much of the existing literature revolves around institutional strategies, policy interpretations, or pedagogical theory, examined within formal settings: teacher education programs, syllabi, classroom practices. One major gap is the lack of nationwide, longitudinal studies to understand the impact of NEP, especially in terms of wider public engagement. The present study attempts to bridge this gap by examining Google Trends data from 2015 to 2024 and understand the impact of the 2020 policy intervention.

Online search behavior offers indirect but valuable insight into how deeply educational reforms filter into public awareness. This is premised on the information-seeking behavior theory which posits that individuals seek information on a topic of perceived importance, often via online searches, when they need some information (Case & Given, 2016; Wilson, 1999). Information need can arise due to various factors including public debates, discussions, or the launch of new policies which brings such ideas into the public focus. We hypothesize that the launch of NEP 2020 and subsequent public discourse brought into sharp focus many issues and paradigms including experiential learning. This sparked greater interest in the topic, leading to more online searches regarding experiential learning. The study examines eight experiential learning–oriented online search terms, organized into two thematic dimensions: core ELT principles and ELT-inspired instructional models. Using interrupted time series (ITS) analysis, the study examines whether the release of NEP 2020 guidelines is associated with significant changes in public interest in experiential learning.

II. LITERATURE REVIEW

A. Experiential Learning Theory

Experiential learning is a widely recognized educational framework that emphasizes learning through direct experience. It posits that individuals learn best not just by hearing or reading, but by actively doing, reflecting on those actions, and then applying what they've learned to new situations. Among the most influential contributors to this field is David Kolb (1984), who proposed a four-stage cyclical model, experiential learning theory (ELT): concrete experience (doing or encountering something new), reflective observation (thinking about the experience), abstract conceptualization (forming general ideas or theories), and active experimentation (testing these new ideas in different situations).

ELT's advocacy for immersive teaching methods and real-world case studies, which foster critical thinking, has proven beneficial for learners across various domains. The efficacy of ELT has been well-documented across various educational levels, including primary schools (Chan, 2012; Payne & Costas, 2021), middle schools (Scogin *et al.,* 2017), and higher education (Kolb & Kolb, 2005; Kolb & Kolb, 2017). Research also extends to specific outcomes, such as its impact on children's eating habits and physical activity (Varman et al., 2021; Varman et al., 2023). Prior studies have also examined related dimensions of learner motivation and autonomy, such as applications of Self-Determination Theory in Asian and non-Asian educational contexts (Perera, 2022) and institutional practices of Self-Directed Learning in higher education (Abeyrathne & Ekanayake, 2021). Overall, ELT is a well-researched construct with demonstrable positive outcomes, thus its prominence in the NEP is unsurprising.

The NEP 2020 frequently references concepts related to experiential learning. It emphasizes the integration of experiential learning across all subjects. Importance is given to initiatives like art-integration and sports-integration: whereas art-integration is intended to "strengthen the linkages between education and culture," sports-integration is intended to "promote physical and psychological well-being while also enhancing cognitive abilities" (MHRD, 2020, pp. 11-12). For this reason, ELT is adopted as the theoretical framework for this study. By analyzing public interest in ELT-aligned concepts, the study can systematically examine the degree to which NEP 2020's ideals have percolated into public consciousness.

B. Measuring Policy Intervention Impact

To evaluate the effects of policy interventions, researchers rely on quasi-experimental methods like ARIMA models with intervention terms (Menchetti *et al.,* 2023), Bayesian Structural Time Series (Brodersen *et al.,* 2015), and Difference-in-Differences (DiD) approaches (Athey & Imbens, 2018), and Interrupted Time Series (ITS) with segmented regression (Bernal *et al.,* 2017). For this study we have adopted ITS, since it is particularly well-suited for evaluating the longitudinal effects of policy interventions involving a single population and a clearly defined intervention point. Segmented regression is a particularly prominent and versatile method that models time as a predictor to quantify the structural breaks that follow interventions (Schaffer *et al.,* 2021). This approach specifically measures the pre-intervention trend, immediate shifts in level, and the subsequent post-intervention trend (Kontopantelis *et al.,* 2015). ITS has been extensively validated in policy evaluation across diverse fields, including education, economics, and health systems (Jiang, 2024; Linden, 2015; Shadish *et al.,* 2002). It has demonstrated usefulness for a wide range of real-world problems: assessing road safety in Ethiopia (Abegaz *et al.,* 2014), evaluating alcohol control measures in Lithuania (Štelemėkas *et al.,* 2021), and examining the impact of COVID-19 lockdown policies in India (Thayer *et al.,* 2021).

C. Google Trends

Google Trends (GT) is a widely used tool offering readily available data on Google search queries aggregated by location and time. GT allows users to compare the popularity of search terms across different time periods and against other terms. GT's main output is time series data for the Search Volume Index (SVI), which reflects the relative popularity of a search term, among a set of other search terms, normalized to a peak value of 100 within the specific time and region (Cebrián & Domenech, 2024). A score of 100 denotes peak popularity within the specified measurement period and set of terms, a value of 50 indicates half the peak popularity, and so forth.

Although traditionally used by digital marketers and content creators, GT has been found to be a useful data source for social scientists due to its extensive geographical reach and cost-effectiveness vis-à-vis surveys and other traditional research instruments (Mellon, 2013). It has been used in diverse areas including unemployment rate (Adu *et al.,* 2023), global human rights discourse (Dancy & Fariss, 2023), healthcare (Nuti *et al.,* 2014), AI literacy (Mukhopadhyay, 2024), infodemiology (Mavragani & Ochoa, 2019), and energy consumption (Fu & Miller, 2022). Some concerns have been raised about the accuracy and bias in GT data pertaining to the sampling process employed by Google to compute SVIs. Studies based on low-frequency search queries are more prone to error and reduced reliability. In general, while there may introduce inconsistencies, it does not invalidate GT as a viable data source for social and economic analysis (Cebrián & Domenech, 2023).

III. METHODOLOGY

This study conducts a quantitative analysis of Google Trends (GT) search data for keywords aligned with experiential learning. It adopts Experiential Learning Theory (Kolb, 1984) as the primary theoretical framework. To operationalize this framework, eight search terms were selected and thematically grouped into two categories (Figure 1): core experiential learning concepts and ELT-aligned pedagogical models. The first group, core experiential learning ideas, includes terms like 'experiential learning,' 'experiential education,' 'learning by doing,' and 'hands-on learning.' These terms capture the foundational philosophy and direct practices rooted in ELT. The focus is on how hands-on experience is central to learning.

The second, ELT-aligned pedagogical models, consists of ‘project-based learning’, ‘inquiry-based learning’, ‘case-based learning’, and ‘practice-based learning’. These terms reflect methods derived from or strongly informed by ELT. They encapsulate the operationalization aspect of experiential principles within classroom and institutional settings. These methods embody the full ELT cycle (Concrete Experience → Reflective Observation → Abstract Conceptualization → Active Experimentation), but are not limited to it and may also draw from constructivism or problem-based learning traditions.

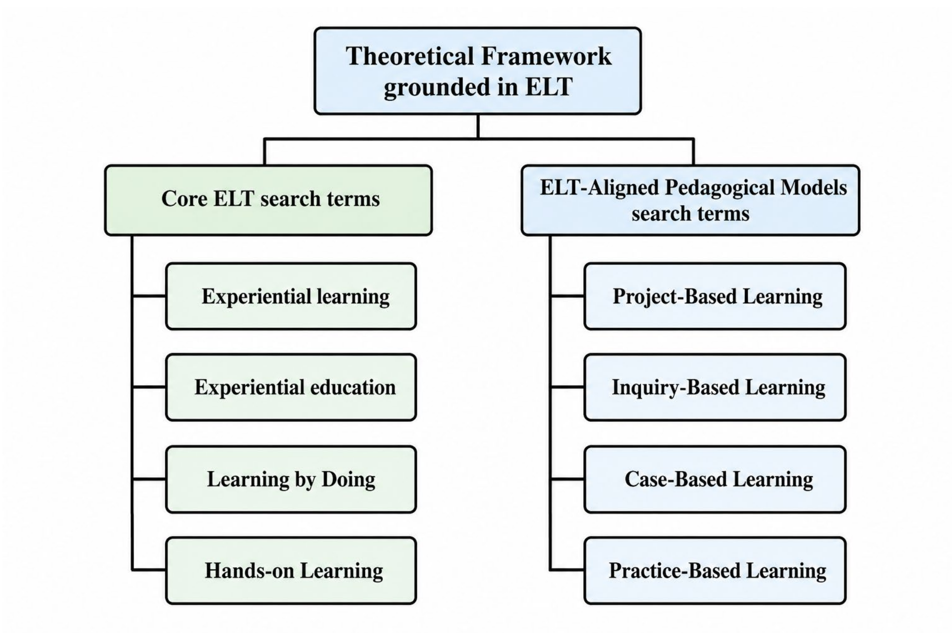

Fig.1 Theoretical Framework Grounded in Experiential Learning Theory (ELT)

By monitoring the monthly search volumes of these terms using GT, the study captures nation-wide trends in public interest related to experiential learning. Data is collected over a ten-year period, from January 1, 2015, to December 31, 2024, yielding a total of 120 time points for each term. A ten-year window offers a balanced lens—broad enough to smooth out short-term noise, yet focused enough to trace meaningful shifts.

To ensure consistency in GT data, it is preferred to perform a single query for the entire period for all the eight chosen keywords simultaneously. This guarantees that all the terms are correctly scaled against each other and with respect to geography and time period. However, given the fact that the online interface allows a maximum of 5 search terms to be compared, the data in the study is downloaded in two batches of four items each. Multiple batches can lead to scaling mismatches because each is independently normalized to its highest search interest. The implication is that relative values for even the same term can differ significantly between batches. To resolve this discrepancy, a common anchor term is used in each batch to re-normalize the data, bringing all separate queries onto a single, consistent comparative scale (West, 2020).

Ideally an anchor term is one whose search volumes have remained relatively stable through the period 2015-2024. It should be relevant to the overall domain but not necessarily be one of the primary terms of interest. After experimenting with different terms, the term “school syllabus ncert” was chosen (Figure 2). The term selected is related to the field of education and exhibits a moderate relative search volume. This ensures that it neither overshadows the study's primary terms nor introduces normalization errors through excessively low volumes.

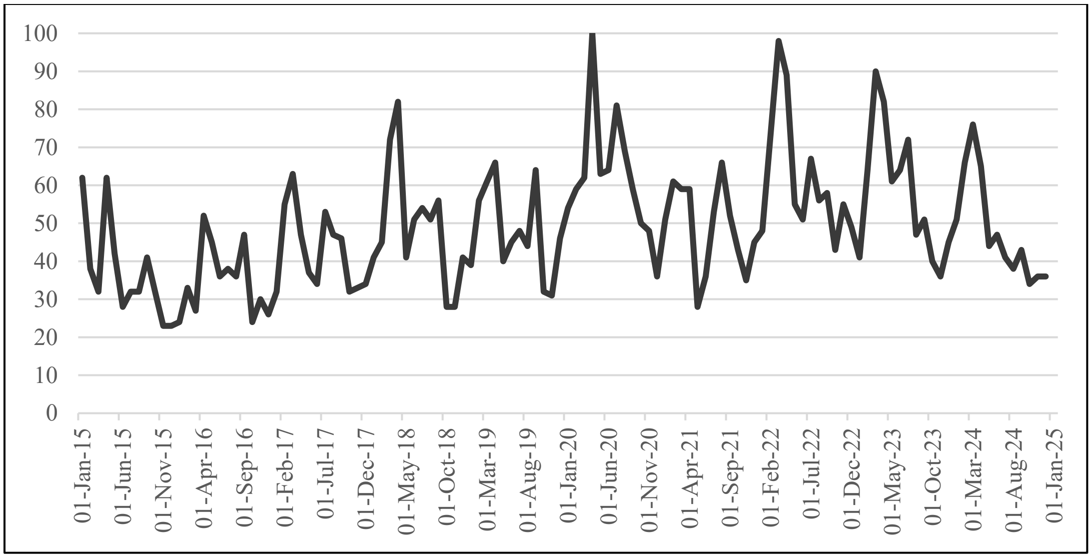

Fig.2 Google Trends: Anchor Term “School Syllabus Ncert” (2015-2024)

Following data collection and re-normalization, the two composite indices are computed. Core ELT composite index is calculated as the average Search Volume Index (SVI) of 'experiential learning,' 'experiential education,' 'learning by doing,' and 'hands-on learning.' Similarly, ELT-Aligned Pedagogical Models composite index is computed by averaging the SVIs of 'project-based learning,' 'inquiry-based learning,' 'case-based learning,' and 'practice-based learning.' While these eight search terms individually maintain sufficient search volume, averaging multiple terms to form a composite indicator enhances the reliability of the trend data and helps mitigate noise inherent in GT data. The resulting two composite indicators are then analyzed using Interrupted Time Series (ITS) analysis based on segmented regression. This approach enables the assessment of shifts in public engagement with experiential learning philosophy and pedagogies, before and after the introduction of NEP 2020.

IV. RESULTS

A. Visual Inspection

The data for the two trend factors—core ELT, and ELT-aligned pedagogical models—are presented graphically in Figures 3. Visual analysis reveals an upward trend in both constructs: core ELT as well as ELT-aligned pedagogical models. This shift becomes more pronounced following the introduction of the NEP in July 2020. Results also indicate that relatively more searches were made for core ELT concepts compared to ELT-aligned pedagogical models. This suggests that public engagement is stronger with foundational ideas of experiential learning than with specific pedagogical strategies. This could be reflective of a broader conceptual curiosity. It is possible that public interest may not yet have been fully translated into interest in applied pedagogical models.

Visual inspection also indicates that the uptick in interest in these ELT-related constructs commenced slightly prior to official release in July 2020. As evidenced by Google Trends data for the term "National Education Policy" (Figure 4), significant public discussion around national education policy began approximately a year before its formal launch. This coincided with the launch of the Draft New Education Policy (DNEP) in June 2019 when it was released to the public domain and wider feedback was sought (Roy, 2022). This was followed by widespread editorials, debates and discussions in print media, television and online platforms. Public interest in experiential learning related concepts gained momentum during this pre-launch period and sustained its upward trend following NEP 2020’s official launch in 2020. It is worth noting that "National Education Policy" as a term encompassed broader discussions even prior to the 2020 reform, though the latter represents a major recent development, and thus we observe peak interest during the June to August 2020 period.

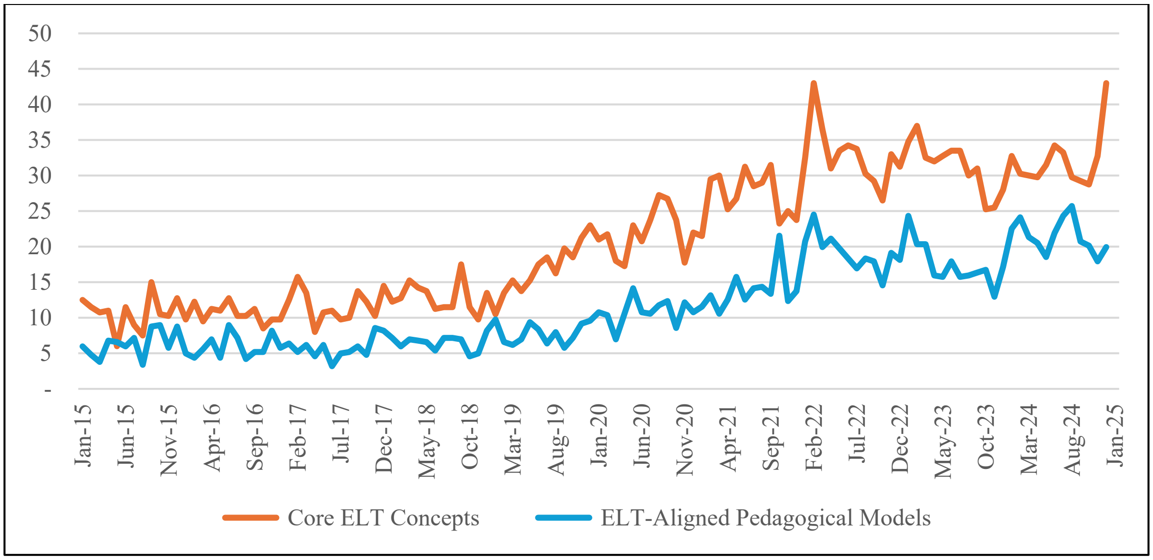

Fig.3 Google Trends: Core ELT And ELT-Aligned Pedagogical Models Composite Indices (2015-2024)

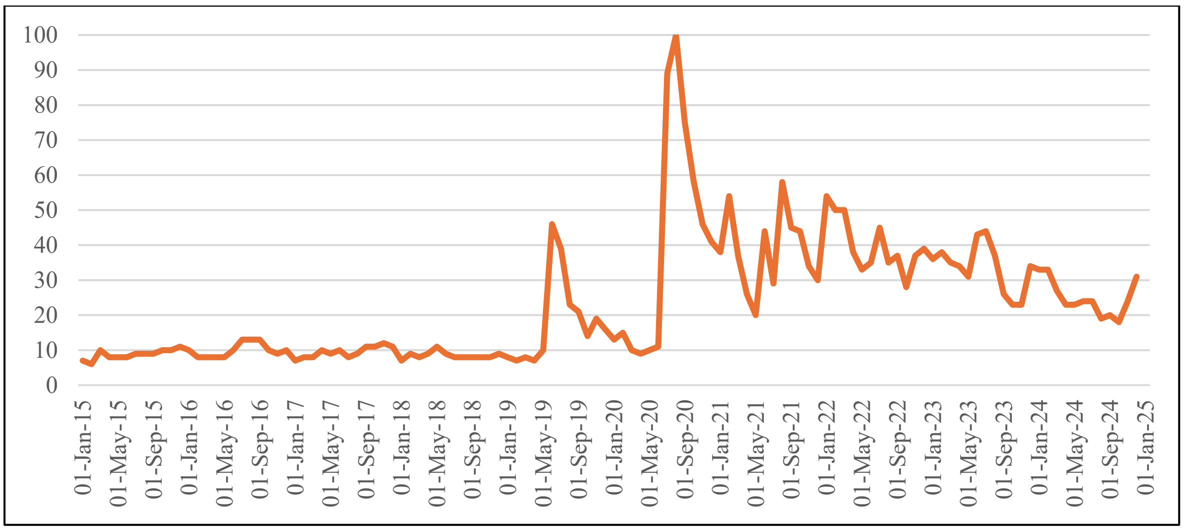

Fig.4 Google Trends: National Education Policy (2015-2024)

B. Interrupted Time Series

Next a quantitative analysis using Interrupted Time Series (ITS) is conducted to evaluate whether the trends reflect a statistically significant and policy-specific impact. This helps determine whether the observed increases are consistent and meaningful over time, rather than the result of random fluctuations. For the purpose of the study, the interruption point is taken as December 2019, mid-point between the release of the draft and final policies.

1. Core ELT: The results of ITS for the Core-ELT composite index is presented in Table I. The analysis shows a statistically significant upward trend in public interest in core ELT trend after the policy intervention (Figure 5). Although there was already an existing positive trend prior to the policy, the intervention led to a sharp and immediate increase in search volumes. This upward trend continues, suggesting sustained engagement post-policy. The model explains almost 86% of the variance, indicating a strong overall fit. It may therefore be said that NEP 2020 positively reinforced an already growing engagement with core-ELT approaches.

TABLE I INTERRUPTED TIME SERIES REGRESSION RESULTS FOR CORE-ELT COMPOSITE INDEX

Parameter	Estimate	Std. Error	t-value	p-value	Significance
Intercept	8.166	2.488	3.282	< .001	Yes
Time (Pre-NEP Trend)	0.304	0.072	4.213	< .001	Yes
Intervention (Level)	20.079	3.445	5.829	< .001	Yes
Time After Intervention	0.209	0.099	2.101	0.038	Yes

Model Fit:
Residual Standard Error: 9.434 (df = 116)
Adjusted R^2: 0.863
F-statistic: 249.9 (df = 3, 116), $p < .001$

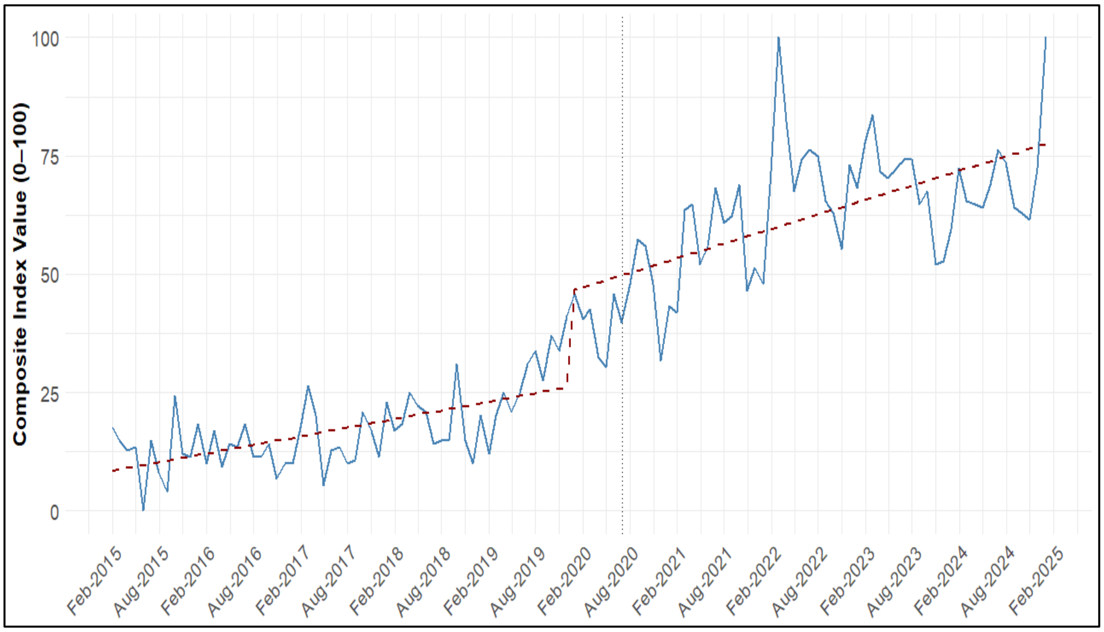

Fig.5 Interrupted Time Series of Core ELT Composite Index

2. ELT-Aligned Pedagogical Models: The results of ITS for the ELT-aligned pedagogical models composite index are presented in Table II. The analysis indicates a sharp and immediate rise in public interest with the introduction of NEP 2020 (Figure 6). At the same time, there is no evidence to suggest that the search interest was increasing or decreasing in any meaningful way before the intervention. In practical terms, the pre-policy trend was flat or weak, and most of the variation in search interest likely began after the intervention. Overall, the model explains a substantial 84.7% of the variation in indicating a very good fit.

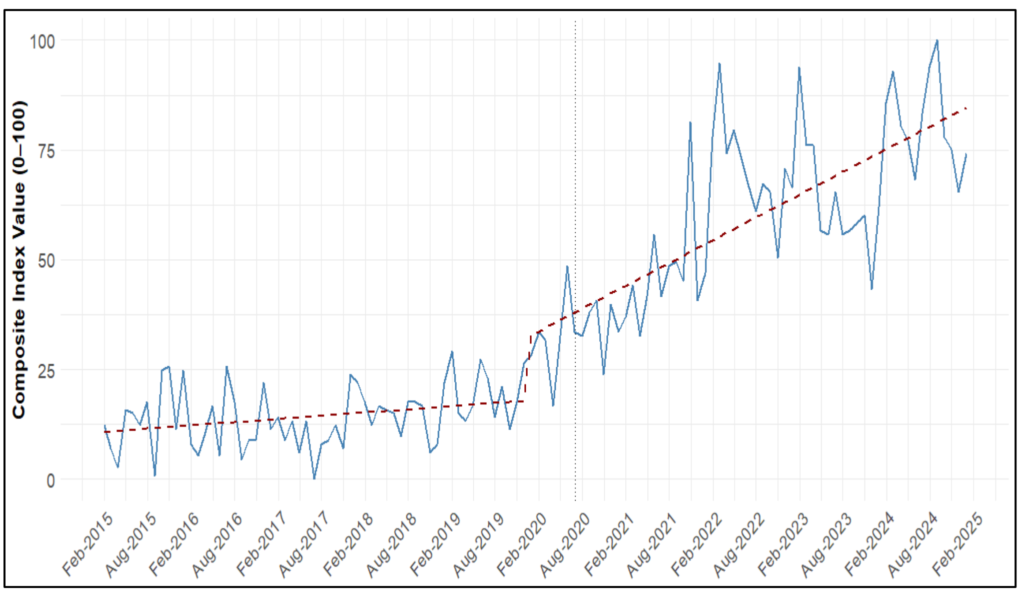

Fig.6 Interrupted Time Series of ELT-Aligned Pedagogical Models Composite Index

TABLE II INTERRUPTED TIME SERIES REGRESSION RESULTS FOR ELT-ALIGNED PEDAGOGICAL MODELS COMPOSITE INDEX

Parameter	Estimate	Std. Error	t-value	p-value	Significance
Intercept	10.704	2.822	3.793	< .001	Yes
Time (Pre-NEP Trend)	0.121	0.082	1.481	0.141	Not Significant
Intervention (Level)	14.092	3.907	3.607	< .001	Yes
Time After Intervention	0.743	0.113	6.583	< .001	Yes

Model Fit:
Residual standard error: 10.7
Adjusted R-squared: 0.847
F-statistic: 214.0 (df = 3, 116), $p < .001$

V. DISCUSSION

The results indicate a sharp and sustained rise in public interest in India in both core ELT concepts and ELT-aligned pedagogical models following the introduction of the NEP 2020. This finding supports our hypothesis grounded in Information Seeking Behavior theory. The launch of the draft policy in 2019, followed by the final policy in 2020, with its focus on experiential and holistic education, saw sustained public debates and extensive media coverage. Along with subsequent implementation guidelines in various institutions, it collectively rendered experiential learning a prominent topic of interest. This likely prompted the wider public to seek information online, resulting in increased search volumes for terms and ideas related to experiential learning. While interest increased in both categories, the relative interest remained higher for core ELT concepts. This pattern suggests that while the policy successfully ignited broader public curiosity about the underlying philosophy of learning by doing, the understanding and discussion around its more detailed instructional strategies may still be evolving. It was also observed that core ELT ideas exhibited a pre-existing upward trend even prior to the policy's release, whereas no such significant pre-intervention trend was observed for ELT-aligned pedagogical models. Overall, these findings suggest a growing public engagement with experiential learning approaches within India's educational discourse in the decade, 2015-2024.

The increased public interest in experiential learning ideas across India is not surprising given its cultural connotations. In the pre-modern Indian context, experiential learning was deeply interwoven with the societal fabric. The indigenous *gurukula* system of education inherently integrated life skills, self-discipline, and practical experiences. As late as 19th-century India, indigenous schools were often integrated with local communities, allowing students to apply their knowledge directly to social contexts such as agriculture or trade. Similarly, a strong emphasis was placed on crafts and vocational learning (Dharampal, 1983). Even Indian arithmetic and sciences, have historically been premised on real-life problem-solving applications. The focus was always on practical mathematics and scientific benefit rather than abstract theorization. This allowed Indian scientists "to develop appropriate theoretical frameworks and procedures, which were continuously tested and refined in practice" (Srinivas, 2022, p.36). Therefore, the inclusion of experiential learning constructs in the NEP 2020 can be seen as a reaffirmation of these long-standing indigenous practices which had been disrupted by colonial rule.

This study, while offering valuable insights, has some limitations. First, its reliance on Google Trends (GT) data inherently reflects public online search interest and discourse, rather than actual pedagogical adoption or institutional implementation. This methodology cannot establish a direct causal link between search queries and genuine learning practices or classroom shifts. Nor can it distinguish between curiosity, advocacy, or critique within search patterns. Second, the analysis is based on a limited set of eight keywords, which may not fully capture the complete spectrum of experiential learning concepts. Third, beyond the specific policy intervention of NEP 2020, other broader contextual factors—global educational trends, and the increasing proliferation of Artificial intelligence (AI) in education—could also have influenced public interest in experiential learning methodologies during the study period. Despite these limitations, the study provides crucial insights into public engagement with experiential education concepts in India and highlights the impact of the NEP 2020 policy intervention. Future research could broaden keyword selection and explore connections between public interest and on-ground implementation. Longitudinal and mixed-method studies may help examine how public curiosity translates into actual policy uptake and classroom practice. A comprehensive nationwide evaluation of learning model adoption—using large-scale surveys, teacher interviews, classroom observations, curriculum reviews, or assessment data—could offer critical perspective on how educational reforms translate into practice.

VI. CONCLUSION

This study investigated shifts in public interest concerning experiential learning approaches in India, leveraging Google Trends data from 2015 to 2024. Grounded in Experiential Learning Theory, the findings reveal that the National Education Policy (NEP) 2020 significantly boosted public online interest in experiential learning overall. A notable observation was that public interest remained considerably higher for fundamental experiential learning concepts compared to specific teaching models that put these ideas into practice. This suggests that growing public interest about ELT ideas hasn't yet led to widespread interest in the practical teaching strategies. As India continues its ambitious education reform, analyses of digital indicators like online search behavior offer invaluable insights. Such studies can help policymakers and educators gauge public reception. They can help monitor how reform ideas are impacting society, ensuring that educational progress reflects public involvement and societal needs.

Declaration of Conflicting Interests
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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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