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Topic Cluster Architecture and Search Intent Mapping as Determinants of Topical Authority: Empirical Evidence from Vocational Certification Platforms in Indonesia

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Abstract

Background: *The shift toward semantic and AI-generated search has made topical authority key to organic visibility, yet empirical evidence from actual performance data in Indonesian-language search remains limited..* ***Objectives:*** *This study measures the empirical contribution of Topic Cluster architecture and Search Intent mapping to the organic performance of an Indonesian vocational certification platform, and tests the significance of differences between clustered and non-clustered pages.* ***Method*****:** *A quantitative explanatory comparative case study of ditekindo.co.id used Google Search Console data on 1,035 active pages over two six-month periods (May 23, 2025–May 22, 2026), analyzed with the Mann-Whitney U and Wilcoxon Signed-Rank tests.* ***Result:*** *Results show BNSP cluster pages have a mean page-level CTR of 0.82%, significantly higher than non-clustered pages (0.24%; U = 115,902; p = 0.008), with a small effect size (r = 0.082). Content Creator (CTR 1.27%) outperformed Digital Marketing (CTR 0.51%), suggesting that intent mapping quality is more determinant than content quantity. Noindexing 20 intent mismatch pages was followed by an increase in mean daily CTR from 2.34% to 3.18%, largely a mechanical effect, as absolute clicks remained stable.* ***Conclusion:*** *In conclusion, integrating Topic Clusters with Search Intent mapping is associated with more efficient organic performance and provides a replicable data-driven content audit procedure.*

INTRODUCTION

The development of the digital search engine ecosystem has entered its most transformative phase since the launch of the World Wide Web. Google's launch of Search Generative Experience (SGE) in May 2023, which later evolved into AI Overviews in 2024 with global coverage, fundamentally changed the paradigm of user interaction with online information: from a link-based navigation model to a direct answer synthesis model generated by the Large Language Model (Ai et al., 2023; Guha et al., 2016; Ziakis & Vlachopoulou, 2024). This change is not just an interface update, but rather a redefinition of what is meant by 'visibility' in the digital search space. Empirically, generative search engines operating in 2023 have presented complete synthesis answers with source citations directly to users, although not all of the statements generated are fully supported by the cited sources (Liu et al., 2023).

Longitudinal analysis of Google's search results page archive shows that SERPs are no longer a list of 'ten blue links', but instead contain direct answer features such as featured snippets and knowledge panels that have the potential to absorb clicks, so users increasingly get answers without visiting external websites (Oliveira & Lopes, 2023). In Indonesia, equivalent zero-click search data is not yet publicly available, and indexed studies on digital marketing in Indonesia still measure digital marketing capabilities through business surveys, not the impact of SERP changes on organic traffic (Zahara et al., 2023). Oliveira & Lopes (2023) asserts that this change in the layout of the SERPs demands a re-evaluation of a measure of success that rests solely on ranking lists; in this landscape, position on the first page no longer guarantees the acquisition of clicks if the content does not have the topical authority that the algorithm recognizes (Jansen & Booth, 2010; Ortiz-Cordova & Jansen, 2012).

Studies of language model-based search systems reinforce this pattern: when search engines present synthesised answers directly, users lose the opportunity to search, compare, and evaluate original sources, thus weakening the role of traditional search result links (Shah & Bender, 2022). Indonesia is one of the largest internet markets in the world, with the number of internet users reaching 202.6 million people or 73.7% of the population (Masrianto et al., 2022). Google dominates the Indonesian search engine market with a share of over 90%, making Google's algorithmic dynamics the main determinant of the visibility of Indonesian-language content.

In this context, a shift towards topical authority evaluation was introduced through updates based on the BERT language model (Guo et al., 2022), framework E-E-A-T dalam Search Quality Evaluator Guidelines (Google, 2023), and strengthened by AI Overviews has a direct impact on Indonesia's digital platform content strategy (Guha et al., 2016; Roumeliotis & Tselikas, 2022; Ziakis et al., 2019). The urgency of this research rests on three interrelated gaps. First, empirical gaps: the majority of studies on Topic Clusters and Search Intent are conceptual-prescriptive or based on practitioner surveys that measure perceptions, not verifiable real performance results (Malaga, 2010; Ziakis et al., 2019; Ziakis & Vlachopoulou, 2024). As far as the author's search goes, no studies have been found that use actual Google Search Console data with formal statistical testing to measure the impact of Topic Cluster implementations empirically.

Second, the contextual gap: almost all of the empirical research that exists comes from the context of the English-speaking market, so it cannot be generalized directly to the Indonesian-language search ecosystem that has distinctive user behavior characteristics, competition structures, and intent patterns (Broder, 2002; Jiang et al., 2019; Ortiz-Cordova & Jansen, 2012). Vocational certification platforms that have a highly structured topic taxonomy following the official BNSP scheme represent an ideal case for testing the effectiveness of cluster architectures as their content hierarchy can be systematically mapped into a Hub-and-Spoke model.

Third, methodological gaps: case studies of BNSP certification platforms provide a unique context in which user intent moves measurably from an informational stage ('what is BNSP certification') to a transactional ('how to register for BNSP certifications') journey that can be quantified through per-page CTR data. Empirical documentation of this intent journey, combined with formal statistical analysis, has the potential to produce a framework that can be replicated by researchers and other practitioners (Jansen & Booth, 2010; Roumeliotis & Tselikas, 2022; Yin, 2014).

The study of semantic SEO and content architecture has evolved significantly since the transition of keyword-based algorithms to semantic understanding. Ziakis et al. (2019) identified important factors in Google search rankings through an analysis of 200 websites, concluding that internal link structure and semantic relevance of content are more consistent predictors of ranking than keyword density alone. Malaga (2010) document the evolution of SEO strategies from a keyword-manipulation-based black-hat approach to a structural approach that prioritizes content quality and site architecture. Jansen & Booth (2010) empirically demonstrates that search intent directly influences a user's click behavior in the SERPs, laying the foundation for an understanding of the importance of content alignment with intent.

Broder (2002) In his seminal study of the taxonomy of web search, it classified queries into three fundamental categories that later became the industry standard. Ortiz-Cordova & Jansen (2012) Extending this taxonomy by showing the correlation between the accuracy of intent classification and conversion rates, provides an economic justification for investing in intent mapping. Joachims et al. (2007) prove that implicit click signals including CTR are accurate feedback to evaluate the relevance of content, which then becomes the basis for understanding why intent alignment directly affects organic performance. Jiang et al. (2019) then proposed a co-cluster hypothesis that showed that documents relevant to queries with similar intent tended to rank consistently on the search engine side; the study used this hypothesis analogously as a basis to test whether pages grouped in a single topic cluster on a single site showed more consistent performance patterns.

Research on SEO in the Indonesian context is still very limited in the indexed academic literature. Ziakis & Vlachopoulou (2024) examines the role of artificial intelligence in SEO but focuses on the European market. Oliveira & Lopes (2023) documenting the evolution of Google's SERP feature longitudinally but does not measure user click behavior, especially in the Indonesian market. Masrianto et al. (2022) provide context for the adoption of a company's digital marketing in Indonesia, including SEO, but does not specifically measure organic search performance. Zahara et al. (2023) examine the digital marketing capabilities of SMEs in Indonesia but based on perception surveys, not verifiable performance data. This gap makes actual GSC data-driven research on the Indonesian platform a distinctive and valuable contribution to the corpus of literature (Guha et al., 2016; Guo et al., 2022; Roumeliotis & Tselikas, 2022).

Based on the literature review, there are four research gaps that have not been adequately addressed. The first gap is the absence of actual GSC-based empirical data: all available studies using perception surveys, laboratory experiments, or SERP analysis without access to verifiable internal performance data. The second gap is the absence of formal statistical testing: claims about the effectiveness of Topic Clusters are generally anecdotal or based on case studies without significance tests. The third gap is the Indonesian linguistic context: the Indonesian language search ecosystem has characteristics that have not been studied in the academic literature (Broder, 2002; Jiang et al., 2019; Ortiz-Cordova & Jansen, 2012). The fourth gap is the absence of empirical documentation on the phenomenon of intent mismatch and its quantitative impact on the efficiency of the aspect domain that has so far only been conceptually discussed in the literature without verifiable performance data.

The novelty of this research lies in three aspects that cumulatively distinguish it from previous research. First, this study uses actual GSC data rather than simulations or surveys from 1,262 indexed pages, with 1,035 active pages as the main unit of analysis, over two

six-month periods, providing an empirical basis that has never been used in similar studies in Indonesia. Second, this study documents the noindex interventions that were actually applied to the platform, along with daily monitoring data before and after the intervention, in the context of the Indonesian-language search ecosystem.

Third, the documentation of the phenomenon of intent mismatch with the quantification of its impact on domain efficiency is a methodological contribution that can be adopted by other researchers as a data-based content audit procedure. The application of non-parametric tests (Mann-Whitney U and Wilcoxon Signed-Rank) is positioned as a statistical validation procedure for cluster effectiveness claims that have so far only been descriptive, not as a methodological novelty in itself (Joachims et al., 2007; Malaga, 2010; Roumeliotis & Tselikas, 2022).

Based on the empirical, contextual, and methodological gaps that have been identified, this study has three main interrelated objectives. First, this study aims to measure the empirical contribution of the Topic Cluster architecture based on the BNSP certification scheme to the organic performance of ditekindo.co.id by comparing the difference in CTR between cluster and non-cluster pages, and to test the statistical significance of these differences using the Mann-Whitney U and Wilcoxon Signed-Rank non-parametric tests on Google Search Console data over two six-month periods. Second, this study aims to analyze variations in CTR performance between certification sub-clusters to identify the extent to which Search Intent mapping quality rather than content quantity is a more fundamental determinant of click efficiency, by comparing sub-clusters with high intent precision (such as Content Creator and Microsoft Office) versus sub-clusters with more diffuse intent (such as Digital Marketing).

Third, this study aims to quantitatively document the phenomenon of intent mismatch in non-cluster content and measure the impact of intent reclassification-based interventions (noindex actions) on overall domain click efficiency through daily CTR monitoring before and after the intervention. Overall, these three objectives are designed to produce statistically verified empirical evidence on the effectiveness of integrating Topic Cluster architecture and Search Intent mapping in building topical authority in the Indonesian-language search ecosystem, while providing a methodological framework that can be replicated by researchers and other practitioners in the field of search engine optimization.

In line with these three objectives, the research hypothesis is formulated as follows. H1a: the CTR distribution of BNSP cluster pages is higher than that of non-cluster pages; H1b: the CTR of cluster pages on paired subsets increases significantly from Previous 6 Months to Last 6 Months; H2 (exploratory): sub-clusters with more specific intents show higher average CTRs than sub-clusters with more diffuse intents; and H3: noindex actions against mismatched intent pages followed by a daily increase in domain CTR without a meaningful decrease in absolute clicks.

RESEARCH METHODS

Types of Research

This study uses a quantitative approach with a retrospective observational design, adopting case studies as units of analysis as conceptualized by (Yin, 2018). This design was chosen because it allows for an in-depth analysis of contemporary phenomena in real contexts where the boundaries between phenomenon and context are not always clear

conditions relevant to research on the implementation of digital content strategies that are contextual in nature and cannot be isolated from changing algorithmic environmental factors (Malaga, 2010; Roumeliotis & Tselikas, 2022; Yin, 2014).

To mitigate the inherent limitations of a single case study, this study adopted a comparative case study approach by including two comparative domains from the same vocational certification segment as contextual references: lspdigital.id (479 keywords tracked via Ahrefs) and sertifikasiku.id (173 keywords tracked via Ahrefs). These comparator domains are only used as contextual references to read sectoral position trends, not as a control group, as the available data is limited to keyword positions from Ahrefs and does not include CTR or actual clicks; thus, this design is not intended to isolate the effects of cluster implementations or establish causal relationships (Jiang et al., 2019; Joachims et al., 2007; Ziakis et al., 2019).

Data triangulation was performed from three different sources to strengthen internal validity: Google Search Console as a primary source (performance data per page for twelve months), Ahrefs as a secondary source (competitor position data), and internal optimization logs for the May 2026 period as a tertiary source (documentation of intervention actions and outcomes). The combination of these three data sources provides the cross-validation necessary to ensure the accuracy of the interpretation of the findings (Malaga, 2010; Roumeliotis & Tselikas, 2022; Yin, 2014).

Population and Sample

The research population is all Google-indexed web pages registered in the Google Search Console account ditekindo.co.id, covering 1,262 pages with performance data in a twelve-month period (November 23, 2025–May 22, 2026 as Last 6 Months and May 23, 2025–November 22, 2025 as Previous 6 Months). Of the 1,262 total pages, 1,035 pages (82.0%) had an impression of > 0 in the current period, so they were classified as active pages and became the primary unit of analysis. The entire population was used in the primary analysis (*census sampling*) given its affordable size and complete data availability, avoiding the biases that may arise from random sampling techniques (Jansen & Booth, 2010; Joachims et al., 2007; Yin, 2014).

Of the 1,035 active pages, the classification was carried out into two groups: BNSP cluster pages (n = 749, 72.4%) and non-cluster pages (n = 286, 27.6%). The URL analysis-based classification used 12 marker keywords that reflected the BNSP certification scheme. It should be noted that the 749 cluster pages covered more than just six main sub-clusters (Digital Marketing 141, Data Analyst 107, Web Developer 86, Graphic Design 64, Microsoft Office 33, Content Creator 17 = 448 pages): the remaining 301 pages consisted of pillar pages, general certification landing pages, query variation pages (e.g. certificate title variations), and support pages that contained cluster marker keywords but did not fall into any of the six main sub-clusters.

The Wilcoxon Signed-Rank test (before-after paired analysis), a subset of 176 cluster pages that had a CTR of >0% in both periods was used as a paired sample. It is important to note that this subset was not a random sample but rather a page that had exposure to both periods, so the results of the Wilcoxon test were exposed to selection bias whose direction could not be ascertained and could not be generalized to all 749 pages of the cluster (Broder, 2002; Jiang et al., 2019; Joachims et al., 2007).

It should be acknowledged that keyword-based classification on URLs creates clusterclusters while simultaneously representing the core thematic pages of the BNSP certification, whereas non-clustered groups are dominated by pages outside of the core

topic; therefore, the differences between groups reflect not only the effects of Hub-and-Spoke architecture, but also topic differences, relevance to brands, and query intent. Data on the number of internal inbound links per page is not yet available in this study dataset, so those architecture variables cannot be tested directly.

Table 1. Summary of Population and Research Sample

Components	Remarks	Value
Total indexed pages	Overall population	1,262 pages
Active page (impr > 0)	Main Analysis Unit (Last 6 Months)	1,035 pages
BNSP cluster page	Treatment groups	749 pages (72.4%)
Non-clustered pages	Comparison groups	286 pages (27.6%)
Paired subset (Wilcoxon)	CTR > 0% in both periods	176 pages
Comparator domain 1	lspdigital.id	479 keywords (Ahrefs)
Comparator domain 2	sertifikasiku.id	173 keywords (Ahrefs)
Observation period	Two-period comparative	12 months (6 + 6 months)

Research Instruments

The primary data collection instrument is the Google Search Console (GSC) export interface with Web search type filters, which generates two main datasets: (1) data per page (*Top Pages*) with clicks, impressions, CTR, and average position metrics for Last 6 Months and Previous 6 Months; and (2) data per query (*Top Queries*) with similar metrics. GSC was chosen as the primary instrument because it provides actual performance data collected directly by Google from real user interactions, making it the highest publicly available source of ecologically valid data for organic performance analysis (Joachims et al., 2007; Roumeliotis & Tselikas, 2022).

The secondary instrument is the Ahrefs platform used to extract the organic position data of the comparator domain. Ahrefs uses crawling methods and traffic estimation based on SERP position data combined with search volume, resulting in traffic estimates that are accurate enough for contextual comparison purposes although not as accurate as GSC data sourced from actual user data. The use of two instruments from different sources (GSC for internal data, Ahrefs for competitor data) is a recommended triangulation practice in empirical SEO research (Jiang et al., 2019; Malaga, 2010; Ziakis et al., 2019).

Tertiary instruments are manual SERP analysis-based Search Intent classification protocols adapted from taxonomy Broder (2002) with an extension of four industry categories. The protocol is designed to ensure consistency in classification decision-making: each page is analyzed based on the representative query with the highest impressions in GSC, then the top ten results of Google SERPs are analyzed to identify dominant intent based on the content type, SERP features, and title language used by competitors.

The main limitation of this instrument is the absence of a formal inter-rater reliability check whose validity is confirmed through classification-based intervention outcomes (Broder, 2002; Jansen & Booth, 2010; Ortiz-Cordova & Jansen, 2012). The four categories used are informational, navigational, commercial (investigation before decision), and transactional, which is a taxonomy of three categories Broder (2002) which is extended to commercial categories as is prevalent in industry practice. Because classification has not been performed by two independent raters, inter-rater reliability (e.g. Cohen's kappa) has not been reported; intent precision labels at the sub-cluster level are also established after performance data is available, so such label-based analyses are treated as exploratory interpretations rather than independent testing.

Data Collection Techniques

Primary data collection was carried out through GSC data export on May 23, 2026. The Last 6 Months period in GSC covers approximately November 23, 2025–May 22, 2026, while Previous 6 Months covers approximately May 23, 2025–November 22, 2025. The implementation of the Topic Cluster begins in January 2026, so the Last 6 Months include ≈2 months of pre-implementation (November 23–December 2025) and ≈4.7 months of implementation to post-implementation (January–May 22, 2026).

The January 2026 daily data recorded on exports covers only six days (26–31 January); due to this incompleteness of logging, January is excluded from the monthly trend analysis but is retained in the aggregate dataset. Filters applied: Web search type (excluding Image, Video, News Search), resulting in a dataset of 1,262 rows of data per page processed using Python (pandas, scipy.stats). Daily monitoring data for noindex interventions (13 May–9 June 2026) is retrieved via a separate GSC export after the monitoring period ends, so it is not included in the 23 May 2026 export (Joachims et al., 2007; Roumeliotis & Tselikas, 2022; Yin, 2014).

Secondary data collection from Ahrefs was carried out by entering lspdigital.id and sertifikasiku.id domains into the Ahrefs Organic Keywords report, extracting current and previous position data along with traffic estimates for each tracked keyword. This data was used to confirm sectoral algorithmic trends that may contaminate the interpretation of ditekindo.co.id performance changes. Tertiary data in the form of internal optimization logs for the period 19–22 May 2026 was collected through documentation of noindex actions performed on 20 pages of intent mismatch, along with daily monitoring data from the GSC.

The main metrics of the intervention were the average daily CTR in the windows before (May 13–18, 2026) and after the intervention (May 23–June 9, 2026), which were 2.34% and 3.18%, respectively, with absolute daily clicks and impressions; while the values of 1.27% (February 2026) and 3.01% (May 22, 2026) were daily CTRs at a single point in time that were only reported as complementary information (Jiang et al., 2019; Yin, 2014; Ziakis et al., 2019).

Research Procedure

The research was carried out in four structured stages. The first phase (January–February 2026) was the implementation of the Topic Cluster architecture: identification of two main pillar pages, the construction of six sub-clusters based on the BNSP certification scheme (Digital Marketing 141 pages, Data Analyst 107, Web Developer 86, Graphic Design 64, Microsoft Office 33, Content Creator 17), and the implementation of a two-way internal link network. The second phase (March–April 2026) was the

observation phase: monitoring of organic performance through the GSC without additional intervention to enable the accumulation of algorithmic signals.

The third stage (May 2026) is analysis and intervention: GSC data export, page classification, statistical testing, identification of mismatch intent, and noindex action against 20 pages. The fourth stage is the analysis and reporting of results (Broder, 2002; Roumeliotis & Tselikas, 2022; Yin, 2014). The structure implemented follows a Hub-and-Spoke model: the pillar page links to the spoke page in its sub-cluster, and each spoke page links back to the pillar page; in addition to the six sub-clusters, 301 supporting pages (common certification landing, query variation, and supporting page) are linked to the same structure. Details of the number of internal links per page and the example anchor text are not yet available in this study dataset, so the implementation of the architecture is reported descriptively.

Data Analysis Techniques

The data analysis used two main statistical techniques that were selected based on the characteristics of the CTR data distribution. First, the Mann-Whitney U Test (Wilcoxon rank-sum test) to test the difference in CTR distribution between cluster and non-cluster pages. This non-parametric test was chosen because the web CTR distribution did not follow the normal positively skewed distribution with a long right tail and a minimum value of 0% so parametric tests such as the t-test were not appropriate. The one-sided test was applied with the alternative hypothesis that cluster pages have a higher CTR than non-clusters, with a significance level of $\alpha = 0.05$.

The assumption of non-normality was verified through visual inspection of the histogram and confirmed by the predominance of zero values in both groups (Jiang et al., 2019; Joachims et al., 2007; Malaga, 2010). In this study, two definitions of CTR are distinguished. The aggregate CTR is calculated as Σclick/Σimpressions and is used at the domain level (Table 2), while the group's average CTR is calculated as the weightless arithmetic average of the CTR per page and is used for comparison between groups and sub-clusters (Table 3 and Table 4), since the Mann-Whitney U test unit of analysis is the page.

Second, the Wilcoxon Signed-Rank Test was to test the significance of inter-period CTR changes on cluster pages that had data in both periods ($n = 176$). This paired test was chosen to capture the temporal dynamics of whether the increase in cluster CTR between periods was more than could be explained by random variation. The effect size was calculated using rank-biserial correlation (r) for the Mann-Whitney U test and $r = |Z|/\sqrt{n}$ for the Wilcoxon Signed-Rank test to provide an idea of the magnitude of the practical effect beyond mere statistical significance.

The entire calculation was performed using Python (scipy.stats version 1.11.4), allowing reproducibility by other researchers with the same dataset; anonymized datasets and Python analysis scripts could be obtained from the corresponding authors upon reasonable request. In addition to statistical analysis, comparative descriptive analysis was performed for average position metrics, clicks per page, and intent distribution between sub-clusters (Broder, 2002; Jansen & Booth, 2010; Ortiz-Cordova & Jansen, 2012).

RESULTS AND DISCUSSION

Overall Domain Performance and Two-Period Dynamics

Analysis of GSC data over two six-month periods revealed performance dynamics that reflect the typical characteristics of the new cluster content implementation phase. In the latest period (Last 6 Months), ditekindo.co.id recorded 55,574 organic clicks from 6,675,478 impressions with an average position of 6.62 and an aggregate CTR of 0.83%. Compared to the previous period (71,577 clicks from 5,378,870 impressions, position 7.91, CTR 1.33%), there is a seemingly paradoxical pattern: impressions increased +24.1% but clicks decreased by −22.3%, while the average position improved by +1.29 points. One apparent paradox in the data needs to be reconciled: the domain's CTR dropped from 1.33% to 0.83%, but Wilcoxon's test on 176 paired pages found a significant increase in CTR ($p < 0.0001$).

Both can be consistent: 149 new cluster pages published in January–April 2026 and included in 1,035 active pages Last 6 Months had a low initial CTR, adding a lot of low-CTR impressions to the overall pool that suppressed the domain's CTR, while existing cluster pages (Wilcoxon's subset) experienced an increase in CTR. The increase is consistent with, but has not yet proven, the existence of a cluster halo effect, as alternative explanations such as regression to the mean, sectoral trends, changes in the appearance of SERPs (including AI Overviews), and selection bias in paired subsets cannot be ruled out. This pattern of lag effects of surging impressions, improved positions, and clicks has not followed consistent with the patterns commonly found in the implementation of new cluster content (Jiang et al., 2019; Malaga, 2010; Roumeliotis & Tselikas, 2022).

Table 2. Comparison of Two-Period Domain Performance (Source: Google Search Console)

Metrics	**Previous 6 Months**	**Last 6 Months**	**Changes**
Total Organic Clicks	71.577	55.574	−22.3%
Total Impressions (Impressi)	5.378.870	6.675.478	+24,1%
CTR Agregat Domain	1,33%	0,83%	−0.50 points
Average Position	7,91	6,62	+1.29 positions (improved)
Total Active Pages (Impr>0)	n.a.*	1.035	Increased (including 149 new cluster pages)

Note: Domain CTR is calculated as aggregate CTR (Σclicks/Σimpressions). *The number of active pages in the Previous 6 Months was not reported separately in the analyzed exports; the 1,035 figure refers to the Last 6 Months and has included 149 new cluster pages published January–April 2026.

Proper interpretation of this pattern requires an understanding of the working mechanism of Google's algorithmic evaluation of new content. When domains publish 149 new cluster pages between January–April 2026, Google begins indexing and displaying these pages in SERPs (surging impressions). However, the algorithm needs time to evaluate new page trust signals through the accumulation of click, bounce, and engagement data before it is positioned to be competitive enough to convert impressions into clicks efficiently. An average position increase of +1.29 points may indicate a

positive algorithmic evaluation and ongoing accumulation of topical authority signals, although, as discussed in the following paragraphs, these improvements may at least partially reflect sectoral trends (Guo et al., 2022; Joachims et al., 2007; Roumeliotis & Tselikas, 2022).

Competitor data provides contextual information about sectoral algorithmic trends: lspdigital.id increased from an average of 10.61 to 6.61 (+3.99 points) and sertifikasiku.id from 13.00 to 6.30 (+6.70 points) in the same period. The improvement in the position of the two comparators was greater than that of ditekindo.co.id (+1.29 points), so the improvement in ditekindo.co.id position can be at least partly explained by sectoral trends, and in the case of ditekindo.co.id position improved more slowly than its competitors. In addition, the average position of Ahrefs for tracked keywords is not methodologically equivalent to the average position of GSC, so this comparison is only indicative.

Therefore, the distribution patterns of ditekindo.co.id clicks discussed in the next sub-chapter are not causally attributed to cluster implementations, but rather are treated as associations that require advanced testing with designs that have control groups (Jiang et al., 2019; Malaga, 2010; Ziakis et al., 2019). There is an important note regarding the CTR metric used in this study. The aggregate domain CTR from the full six months of export GSC data (Last 6 Months = 0.83%; Previous 6 Months = 1.33%) is the basis of domain-level analysis in Table 2, while CTR in Table 3 and Table 4 is the weightless average of CTR per page.

The domain CTR on daily monitoring, which is an average daily CTR of 2.34% before and 3.18% after the intervention, as well as single-point values of 1.27% (February 2026) and 3.01% (May 22, 2026), is used specifically to read the short-term impact of the noindex intervention. These metrics measure different things and cannot be directly compared due to differences in the time coverage, how they are calculated, and the composition of the pages measured (Joachims et al., 2007; Roumeliotis & Tselikas, 2022).

Contribution of Cluster Topic Architecture: Statistical Analysis

Of the 1,035 active pages, 749 pages (72.4%) were classified as BNSP cluster pages and 286 pages (27.6%) as non-clustered based on URL analysis with 12 marker keywords. Cluster pages contributed 38,714 clicks (69.7% of the total 55,574 clicks), while non-clusters generated 16,860 clicks (30.3%). The proportion of clicks of this cluster was slightly lower than the proportion of its pages (72.4%), so the cluster's advantage was not seen in the distribution of total clicks, but rather in the efficiency of clicks per impression at the page level. The average (unweighted) CTR of cluster pages of 0.82% substantially outperformed non-cluster's by 0.24% by a difference of +0.58 percentage points or 3.42 times.

This value is the average CTR per page, which cannot be directly multiplied by the total impressions; The aggregate CTR per group (Σclick/Σimpressions) requires the total impressions per group that have not been presented separately in this text. The average position of cluster pages (7.63) is also better than that of non-clusters (9.25), which is consistent with a stronger signal of relevance to Google's algorithm, although differences in topics and intent between groups play a role (Jiang et al., 2019; Joachims et al., 2007; Roumeliotis & Tselikas, 2022).

Table 3. Comparison of Cluster vs Non-Cluster Page Performance (Source: GSC)

Metric	Klaster BNSP (n=749)	Non-Klaster (n=286)	Differences
Total Clicks	38.714 (69,7%)	16.860 (30,3%)	+21,854 clicks
Average CTR (unweighted)	0,82%	0,24%	+0.58 percentage points
Average Position	7,63	9,25	+1.62 better position
Click per Page	51,7	59,0	−7.3 clicks (≈ −12.4%; see note)
CTR Median	0,00%	0,00%	Skewed distribution of both

The Mann-Whitney U test on the CTR distribution of all 1,035 active pages yielded U = 115,902, p = 0.008 (one-sided, α = 0.05). The null hypothesis is rejected: the difference in CTR distribution between cluster and non-cluster pages is statistically significant, not a sampling artifact or random variation. Effect size rank-biserial |r| = 0.082 (positive direction: cluster > non-cluster) is relatively small based on the Cohen convention. It is important to distinguish between statistical significance and practical significance: with n = 1,035 pages, the test has such high power that even small differences result in significant p-values.

The proportion of cluster clicks (69.7%) that is close to the proportion of pages (72.4%) also indicates that this amount cannot be used as evidence of operational excellence. In addition, the median CTR of 0.00% in both groups shows very zero-inflated data, so a two-part analysis, namely the proportion of pages with > 0 clicks and CTR among pages that received clicks, is recommended as a follow-up analysis as these details have not yet been presented in this manuscript (Jiang et al., 2019; Joachims et al., 2007; Malaga, 2010).

The Wilcoxon Signed-Rank test on 176 pages of paired clusters yielded W = 1.919, p < 0.0001, with an effect size r of ≈ 0.65 (Z ≈ −8.67 based on normal approximation, n = 176), indicating a statistically significant increase in cluster page CTR between periods. The significance of the cross-group test (Mann-Whitney) and the paired test (Wilcoxon) showed a consistent pattern, but Wilcoxon's results need to be read carefully because the subset was selected based on a 0% CTR > in both periods, so it can be influenced by selection bias, regression to the mean, sectoral trends, and SERP changes. As far as the researchers are concerned, no similar application of formal statistical tests to the comparison of cluster vs non-cluster performance using actual GSC data in the context of an Indonesian-language vocational certification platform (Broder, 2002; Jiang et al., 2019; Joachims et al., 2007).

Methodological note on clicks per page: higher values in non-clusters (59.0 vs 51.7; difference −7.3 clicks or ≈ −12.4%) need to be interpreted carefully. Non-clusters include some pages with very high click-through volumes but low CTRs due to very large intent mismatch impressions but low conversions. Higher average clicks per page in non-clusters reflect a very uneven distribution (some pages with very high clicks dominate the average), not better engagement quality. Average CTR (0.82% vs 0.24%) is a more

representative indicator of intent alignment quality because it controls for differences in impression volume between pages (Jansen & Booth, 2010; Joachims et al., 2007; Ortiz-Cordova & Jansen, 2012).

Performance Variation Between Sub-Clusters: Intent Quality Supremacy

The most managerially significant finding from this study is not in the comparison of clusters vs. non-clusters in aggregate, but in the performance disparity among the sub-clusters themselves. The variation in average CTR from 0.51% (Digital Marketing, 141 pages) to 1.27% (Content Creator, 17 pages) a difference of 2.49 times indicates that the quality of intent mapping, not the quantity of pages in a cluster, can be a more fundamental determinant of click efficiency.

This pattern is in line with the proposition Guo et al. (2022) that semantic matching is more determinant than lexical matching based on keyword frequency, and propositional Ortiz-Cordova & Jansen (2012) that accurate intent classification correlates with conversions. However, the six sub-clusters accounted for only 5,179 clicks or about 13.4% of the cluster's 38,714 clicks; about 86.6% (33,535 clicks) came from 301 pillar, landing, query variation, and supporter pages, with an average of ±111.4 clicks per page. Thus, the cluster vs non-cluster differences in aggregate are mainly determined by pages outside the six sub-clusters, including high-volume pages such as 'how-to-check-certificate-competence-bnsp', so the specific contribution of the sub-cluster architecture needs to be interpreted carefully (Broder, 2002; Jiang et al., 2019; Joachims et al., 2007).

Table 4. Performance per sub-cluster based on BNSP certification scheme (source: GSC)

Sub-Cluster	Page Overview	Total Clicks	Average CTR (unweighted)	Average Position	Clicks/Pages
Content Creator	17	287	1,27%	9,39	16,9
Data Analyst	107	1.603	0,96%	7,20	15,0
Microsoft Office	33	1.438	0,91%	6,43	43,6
Web Developer	86	748	0,68%	6,82	8,7
Graphic Design	64	539	0,63%	6,32	8,4
Digital Marketing	141	564	0,51%	8,60	4,0

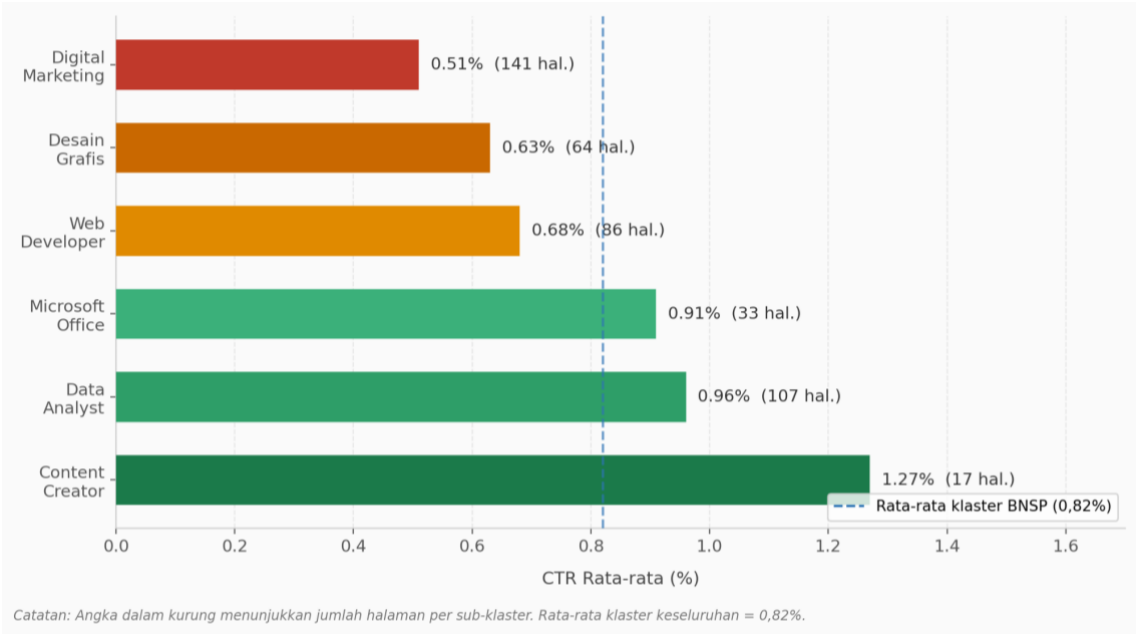


Figure 1. Comparison of Average CTR Between BNSP Certification Sub-Clusters (Last 6 Months, Google Search Console). Dotted line = overall cluster average (0.82%).

The Content Creator sub-cluster recorded the highest CTR (1.27%) with only 17 smallest pages among all sub-clusters. In contrast, Digital Marketing with 141 pages recorded the lowest CTR (0.51%). This quantity-quality paradox can be explained plausibly through SERP analysis: Content Creator pages compete in a more segmented space with queries that have a clear and specific transactional intent to BNSP certification (e.g. 'bnsp content creator certification' with a high CTR because searchers are already highly segmented), while Digital Marketing pages face competition from large-scale educational platforms (*Coursera, HubSpot Academy, Dicoding*) for broad queries such as 'digital marketing' that are not specific to certifications.

This SERP competition factor is a confounding variable that cannot be fully controlled in the design of this study and needs to be recognized as a limitation of interpretation (Broder, 2002; Guo et al., 2022; Ortiz-Cordova & Jansen, 2012). In addition, the differences between sub-clusters have not been statistically tested (e.g. with Kruskal-Wallis tests and post-hoc tests), and the Content Creator sub-cluster consists of only 17 pages, so the intent-based explanation in this section is presented as a plausible explanation, not a tested conclusion.

The Microsoft Office sub-cluster shows an interesting pattern: with only 33 pages, it recorded an average CTR of 0.91% and the highest clicks per page (43.6). This is attributed to the highly structured specificity of Microsoft Office taxonomy and direct overlap with query BNSP certification schemes such as 'excel bnsp certification' (CTR 10.36%) or 'microsoft office bnsp certification' (CTR 9.03%) having highly segmented transactional intents resulting in superior click conversions. Data Analyst (107 pages, CTR 0.96%) showed a good balance between content volume and intent precision, confirming that sub-clusters with structured taxonomy clearly result in more consistent click efficiency (Jansen & Booth, 2010; Joachims et al., 2007; Malaga, 2010).

The visualization of CTR comparisons between sub-clusters in Figure 1 illustrates this disparity explicitly, with the dotted line showing the overall cluster average (0.82%) as a benchmark. Three sub-clusters (Digital Marketing, Graphic Design, Web Developer)

are below the cluster average, while three sub-clusters (Content Creator, Data Analyst, Microsoft Office) are above average. This pattern indicates that a more focused content investment in sub-clusters with high intent precision will result in a greater return on content than content volume expansion in sub-clusters with more diffuse intent. For certification platform managers, this provides initial strategic guidance: prioritize intent depth and precision before volume expansion (Broder, 2002; Jiang et al., 2019; Ortiz-Cordova & Jansen, 2012).

The Phenomenon of Intent Mismatch: Empirical Documentation and Impact Analysis

The phenomenon of intent mismatch, a condition in which published content does not match the dominant intent reflected by the SERPs for the query that generated the page, is very clearly documented in the data of this study. The 'fb-pro-can-make-money' page recorded 803,520 impressions (the highest volume on the entire site) but only 2,617 clicks (CTR 0.33%), although the average page position (4.57) was relatively good. SERP analysis showed that the dominant intent for related queries was commercial-transactional ('how to make money from Facebook Pro'), while the page content was informational.

This mismatch results in negative signals that search engines use to evaluate the relevance of a page on an ongoing basis (Broder, 2002; Jansen & Booth, 2010; Joachims et al., 2007). It should be noted that the 'how-to' pattern is typically classified as informational (how-to), so the commercial-transactional label in this case reflects the author's assessment of the query's monetization orientation, not an independently validated classification. The 0.33% CTR at 4.57 can also be partly explained by the zero-click feature and AI Overviews on the SERPs, so this case is treated as an indication of intent mismatch, rather than a single piece of evidence.

A total of 20 pages were identified to experience intent mismatch based on the classification protocol (CTR < 0.5%, impression > 5,000), with a combined total impression of around 1,094,000 per period and an average CTR of only 0.4%. Intervention actions in the form of noindex on the 20 pages were documented in the optimization log of May 19–22, 2026. The 28-day daily GSC monitoring data (May 13–June 9, 2026, Figure 2) showed that the average daily CTR increased from 2.34% before the intervention (May 13–18) to 3.18% post-intervention (May 23–June 9) an increase of +0.84 points (+36.1% relatively).

It is important to interpret it carefully: daily impressions decreased −28.3% (from 6,928 to 4,966/day) while daily clicks were relatively stable (−3.3%, from 163 to 157/day) meaning that the increase in CTR was largely a mechanical effect of the reduction of the denominator of impressioni. This data provides preliminary evidence that intent-based interventions result in improvements in click efficiency ratios, but strong causal claims require longer observation periods, seasonal control, and separation of arithmetic effects from actual content quality effects (Jansen & Booth, 2010; Joachims et al., 2007).

Therefore, daily absolute clicks were treated as the primary metric in reading the impact of the intervention, and the data showed that the intervention was not followed by a meaningful decrease in clicks. The pre-intervention window of only six days (13–18 May) was also susceptible to weekday and weekend variations; a baseline of at least 28 days and an interrupted time series analysis were recommended for follow-up evaluation (López Bernal et al., 2016). In addition, the daily impressions in this monitoring (±6,928/day) were much smaller than the six-month export daily average (±36,679/day),

and the post-noindex daily impression decline (±1,962/day) was smaller than the estimated 20-page daily impressions (±6,011/day); This difference is likely due to the non-identical scope of export filters (property, country, or device), so the daily figures can only be read as internal indicators and cannot be directly compared to the six-month aggregate.

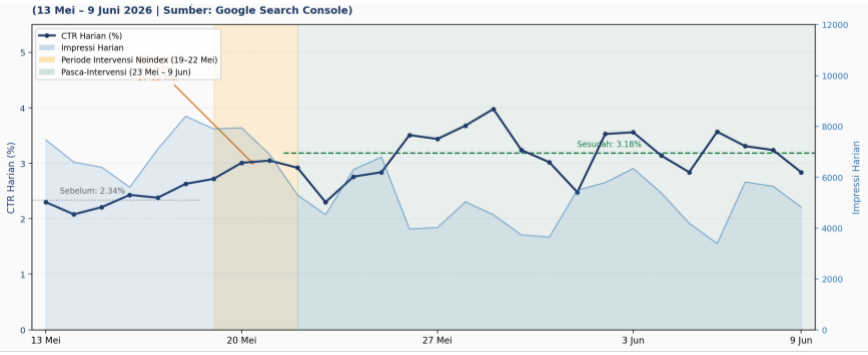


Figure 2. Daily CTR and Impression Trends Before, During, and Post-Intervention Noindex (May 13–June 9, 2026). Orange zone = noindex period (May 19–22); green zone = post-intervention. Source: Google Search Console.

This noindex intervention also coincided with Google's achievement of position 1 for strategic keywords: 'bnsp certification cost' with AI Overview + Sitelinks and 'practical office advance certification'. However, the achievement of these two keywords is anecdotal and is not used as evidence that intent signal cleanup strengthens topical domain authority; it is only consistent with the mechanism proposed in the literature on the influence of content quality signals on algorithmic trust and requires testing on a broader sample of keywords. It is important to note that the increase in CTR from 1.27% to 3.01% is a daily CTR at a specific point in time, different from the six-month aggregate CTR (0.83%) reported in Table 2 both measure different things and cannot be directly compared (Jansen & Booth, 2010; Joachims et al., 2007; Roumeliotis & Tselikas, 2022).

These findings are in line with the proposition Jansen & Booth (2010) that intent misalignment is the main cause of low CTR regardless of ranking position, while supporting the argument Ortiz-Cordova & Jansen (2012) that investing in intent classification precision yields measurable dividends in organic performance. From a content portfolio management perspective, this study indicates that actively managing the quality of intent signals including a willingness to remove content that generates negative signals is a more profitable strategy than maintaining unconverted impression volume.

This implication is particularly relevant in the era of AI Overviews where Google is increasingly using engagement signals as a quality proxy to determine which content is cited in AI synthesis (Ai et al., 2023; Guo et al., 2022; Ziakis & Vlachopoulou, 2024). Nonetheless, these findings need to be compared with evidence suggesting that a drop in clicks can also occur without intent misalignment: Shah & Bender (2022) argue that the presentation of synthetic answers directly reduces user engagement with original sources and traditional search result links, and Aggarwal et al., (2024) suggests that visibility on generative engines is affected by different optimization factors than conventional SERP rankings. Thus, low CTR on high-impression pages does not necessarily indicate intent mismatch, but may also reflect changes in SERP formatting, so these two mechanisms need to be separated in further research.

Top Cluster Page Analysis and Click Efficiency Intent Patterns

Analysis of the highest-performing BNSP cluster pages revealed a pattern consistent with intent mapping theory: the pages with the highest CTRs were dominated by content that aligned with specific transactional or commercial intents. The 'how-to-check-certificate-competency-bnsp' page recorded 10,922 clicks with a CTR of 5.13% at an average position of 2.72 indicating SERP dominance for high-volume transactional queries. The 'bnsp-certification-free' page recorded a CTR of 9.75% (3,559 clicks) and the 'certificate-excel-bnsp' page recorded a CTR of 10.36% (908 clicks) two pages with the highest CTR reflecting commercial intent (cost evaluation) and segmented transactional intent (tool-specific certification) respectively (Broder, 2002; Joachims et al., 2007; Ortiz-Cordova & Jansen, 2012).

Of the top 10 pages by clicks, 7 had transactional intent and 2 had commercial intent of only 1 informational page among the top 10. This pattern is very consistent with the literature that states that the final stage of the user journey results in the highest click conversion efficiency, as users with transactional intent already have a defined motivation and only need confirmation that the page being displayed is relevant to their specific needs. Strategic implications: in the design of a cluster architecture for a certification platform, pages that target specific transactional and commercial intents should be prioritized as the content investment with the highest ROI (Broder, 2002; Jansen & Booth, 2010; Malaga, 2010).

The 'excel-bnsp certification' page with a CTR of 10.36% on 908 clicks demonstrates the power of long-tail keyword targeting in the cluster architecture. The 'bnsp excel certification' query has a lower search volume than broad queries such as 'bnsp certification', but the intent is highly segmented and the SERP competition is much lower. In the cluster architecture, the page acts as a spoke that handles specific long-tail queries while the pillar page handles role-sharing informative broad queries that optimize visibility opportunities at different levels of the intent funnel. This principle is consistent with the content distribution logic in the Hub-and-Spoke architecture as well as the long-term organic keyword selection strategy (Erdmann et al., 2022; Jiang et al., 2019).

These findings are overall in line with the three theoretical propositions that form the foundation of this study, with a number of limitations. First, it is analogous to the co-cluster hypothesis Jiang et al. (2019), a coherent cluster page showed an average CTR 3.42 times higher than non-clusters (0.82% vs 0.24%, $p = 0.008$), although the effect size and topic differences between groups played a role. Second, the proposition Broder (2002) about the classification of intent as a determinant of relevance is supported indicatively: sub-clusters that are assessed to have high intent precision (Content Creator, Microsoft Office) produce the highest CTR, but the precision assessment of intent is carried out after viewing the data and has not been statistically tested.

Third, the findings Joachims et al. (2007) about CTR as a relevance proxy is relevant for interpreting this pattern, noting that CTR is also influenced by ranking position and SERP features. By theoretical implication, the effectiveness of cluster architecture at the site level seems inseparable from intent alignment and page topic relevance; cluster architecture is more precisely seen as a condition that amplifies intent alignment impacts rather than stand-alone determinants (Guo et al., 2022; Ortiz-Cordova & Jansen, 2012; Roumeliotis & Tselikas, 2022).

CONCLUSION

This study showed that Topic Cluster architecture integrated with Search Intent mapping was associated with higher organic click efficiency on Indonesian-language vocational certification platforms. Answering the first objective, BNSP cluster pages had an average CTR per page 3.42 times higher than non-clusters with statistically significant differences, although the effect size was relatively small. Answering the second objective, sub-clusters with more specific intents outperformed large-volume sub-clusters, indicating that intent precision was more decisive than content quantity. Answering the third objective, noindex to 20 intent mismatch pages was followed by an increase in CTR ratios that were mostly mechanical, with absolute clicks relatively stable. Implicitly, certification platform managers are advised to prioritize intent precision and data-driven content audits on a regular basis, while follow-up research requires control groups, longer baselines, and cross-domain replication.

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CONFLICT OF INTEREST

The author declares that there is no conflict of interest in this study, whether financial or non-financial. The author has no employment, consulting, ownership, or other commercial relationship with any ditekindo.co.id or party that could affect the conduct of the research, data analysis, or interpretation of the results. Access to Google Search Console data ditekindo.co.id be used solely for research purposes. All findings are reported objectively, including the small effect size and limitations of the study.

AUTHOR'S CONTRIBUTION

Arulfalah Nurwahid: conceptualization, methodology, implementation of Topic Cluster architecture and noindex interventions, data curation, formal analysis, visualization, and initial draft writing. Aip Kefrian: validation, manuscript review and editing, as well as supervision. All authors have read and approved the final version of the manuscript.

GENERATIVE ARTIFICIAL INTELLIGENCE USAGE STATEMENT

The authors state that generative artificial intelligence (AI) is used in the preparation of this manuscript on a limited basis. AI is used to improve language clarity, improve grammatical structure, and help streamline manuscript writing in the revision process based on reviewer input. AI is not used to generate, modify, or interpret research data, and it is not used to perform statistical analysis.

All data is sourced from Google Search Console and Ahrefs, and statistical analysis is conducted by the author using Python. The use of AI complies with applicable ethical guidelines regarding the use and disclosure of generative AI in scientific research. The entire content of the manuscript, including references, has been reviewed and verified by the author. The author is solely responsible for the accuracy, integrity, and final content of the manuscript.

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