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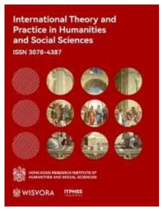

A Multidimensional Evaluation and Comparative Analysis of Artificial Intelligence Application Popularity: Evidence from the UK and US Markets

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Abstract

With the rapid advancement of artificial intelligence (AI) technologies, the adoption and popularity of AI applications vary substantially across national markets. Systematically characterizing and comparing these popularity patterns has therefore become an important research issue. This study develops a multidimensional evaluation framework encompassing technological performance, functional and scenario adaptability, market ecosystem, sociocultural environment, and network effects. Using this framework, the entropy-weighted TOPSIS method is applied to conduct a comprehensive evaluation and ranking of twelve mainstream AI applications in the UK and US markets. In a research context characterized by a small sample size and multiple heterogeneous indicators, the study provides an exploratory assessment of the relative popularity of AI applications.

The results reveal two main findings. First, clear heterogeneity exists across application types: text-based AI applications generally achieve higher composite rankings, whereas image-generation applications display a more dispersed distribution of scores. Second, when benchmarked against user adoption shares in the UK and US markets as a proxy for real-world popularity, the composite evaluation results show a high degree of consistency with observed usage patterns. This consistency suggests that the proposed multidimensional evaluation framework is capable of capturing key features of AI application popularity in practice.

By adopting a composite evaluation perspective, this study avoids the limitations of causal inference under small-sample conditions and offers a quantitative reference for comparative studies of AI applications and market positioning strategies.

1.Introduction

Since AlphaGo defeated the world Go champion and attracted widespread public attention, artificial intelligence (AI) has, within only a few years, completed a striking transition from a "technological showcase" to a set of tools used in everyday life. With the continued evolution of large-scale models and generative AI technologies, AI applications have gradually penetrated a variety of practical domains, such as office collaboration, content creation, and educational assistance. Increasingly, they are becoming digital tools that many people encounter and use in their daily routines. At the same time, however, there are clear and substantial differences in how popular different AI applications actually are in real-world use, including their levels of public acceptance and the extent to which they are adopted and used. In this context, two closely related questions become particularly important: **how to describe and measure the popularity of AI applications**, and **how to understand the mechanisms through which such popularity differences are formed**. These questions have become salient issues that merit careful attention.

In 2025, Future Publishing conducted a questionnaire survey on the most popular AI applications based on several hundred technology consumers in the United States and the United Kingdom. Focusing on twelve AI tools that were used relatively frequently in the market, the survey carried out a systematic statistical description of their usage patterns [1]. Importantly, the survey did not only report the user adoption shares of different AI applications in the UK and US markets. It also presented additional information that helps portray real-world diffusion in a more concrete way, including the composition of user groups, changes in usage frequency, and popularity characteristics across different categories of AI applications. By providing such descriptive evidence, this survey offers an intuitive and direct empirical basis for observing how AI applications spread and become used in everyday settings, and it helps make the real-world "popularity" of AI applications more visible and comparable.

From an academic perspective, existing research generally suggests that the popularity of AI applications is not something that emerges naturally or automatically. Rather, it is shaped by the joint influence of multiple dimensions. On the one hand, technological attributes are widely viewed as an essential foundation that affects innovation diffusion. In the diffusion of innovations theory, Rogers (2003) emphasizes that several characteristics of an innovation—such as relative advantage, compatibility, complexity, trialability, and observability—play a key role in determining how quickly and how widely a new technology diffuses within a social system [2]. In other words, when a technology is perceived as providing clear benefits over alternatives, fits well with existing practices, is not overly difficult to understand, can be tried at low cost, and has benefits that are observable to others, it is more likely to diffuse faster and to a broader range of users. This theoretical perspective highlights why the intrinsic features of AI applications can matter for differences in their popularity and diffusion outcomes.

On the other hand, factors related to institutions and user trust are also important and cannot be ignored. Institutional-based trust theory, proposed by McKnight et al. (2011), points out that legal protections, normative constraints, and broader institutional environments can effectively reduce uncertainty faced by users when adopting new technologies [3]. When users feel that there are stable rules, safeguards, and recognizable institutional arrangements supporting technology use, their perceived risks and doubts can be reduced, which in turn promotes both the adoption of the technology and the willingness to continue using it. This line of research suggests that popularity is not only a function of technical capability, but also relates to whether users can develop sufficient confidence under the institutional and regulatory conditions surrounding technology use.

In addition, whether an AI application can be well matched with specific tasks and practical usage scenarios is often regarded as a crucial condition for building a stable user base. The Task–Technology Fit (TTF) theory developed by Goodhue and Thompson (1995) argues that sustained technology use and improvements in performance can only be achieved when technological characteristics align closely with task requirements [4]. This implies that even if a technology is advanced, it may not lead to stable adoption and persistent use unless it fits what users actually need to accomplish in concrete settings. Therefore, the extent to which an AI application can support users' tasks effectively, and the degree to which it can be integrated into real usage contexts, may substantially shape differences in popularity among applications.

From a broader macroeconomic perspective, external institutional environments and industrial structures can also influence the diffusion paths of AI technologies. Acemoglu and Restrepo (2020) analyze the effects of AI from the perspectives of task substitution and task creation, and discuss how these processes can affect incentives for adoption as well as acceptance of AI technologies [5]. Their analysis provides a macroeconomic explanation that is helpful for understanding why different types of AI applications may face different adoption incentives and acceptance conditions in reality, and why diffusion outcomes can differ across applications.

Taken together, existing studies have explored the adoption and diffusion of AI applications from multiple dimensions, including technological characteristics, user trust and institutional conditions, task compatibility, and broader external environments. However, most of the literature tends to focus either on individual-level adoption intentions or on macro-level analyses of the impacts of AI technologies. In contrast, systematic quantitative characterizations of the **relative popularity differences across specific AI applications in real markets** remain limited. This limitation is especially apparent in research settings where the number of applications under consideration is relatively small, yet the features relevant to evaluation are multidimensional and heterogeneous. In such contexts, it becomes more challenging to provide a structured and comparable quantitative description of popularity differences across applications.

Motivated by this gap, this study attempts to construct a multidimensional evaluation index system and to employ the entropy-weighted TOPSIS method to evaluate and rank the comprehensive performance of AI applications. By doing so, the paper aims to provide a new analytical perspective for describing the popularity of AI applications and for understanding the characteristics through which their popularity is formed.

2.Research Design

2.1 AI Application Popularity and Multidimensional Evaluation Factors

In this study, the popularity of AI applications is primarily characterized by user adoption shares. Specifically, we collect the adoption shares of individual AI applications from samples in the United States and the United Kingdom, and use the average adoption share across the two countries as a reference indicator of an application's relative popularity. This measure is intended to capture, to a certain extent, the overall user coverage of AI applications in major English-speaking markets and to provide an external benchmark for comparing the results of the subsequent composite evaluation.

It should be noted that the adoption share indicator is not employed to construct a causal model in this study, but rather serves as an objective descriptive reference for the real-world popularity of AI applications. Given the limited sample size and the research focus on relative differences across applications, this paper places greater emphasis on the multidimensional performance of AI applications and their relative rankings, rather than on causal inference.

From both theoretical and practical perspectives, the popularity of AI applications is typically shaped by the joint influence of multiple factors. Drawing on existing literature and observed application characteristics, this study structures the key features of AI applications along five dimensions and constructs a corresponding multidimensional evaluation index system.

(1) **Technological Performance and User Experience.** This dimension captures the overall performance of AI applications in terms of response speed, output quality, system stability, and interface usability. Superior technological performance and user experience can enhance user retention [6] and promote diffusion through word-of-mouth effects.

(2) **Functional Utility and Scenario Fit.** This dimension examines whether an AI application can effectively address users' practical needs in specific contexts, whether it is suitable for high-frequency usage scenarios (e.g., office work, content creation, and learning), and whether its functions exhibit a certain degree of irreplaceability [7].

(3) **Market and Ecosystem Factors.** This dimension mainly covers the application's brand influence, promotional channels, pricing strategy and business model, as well as its degree of integration with other platforms or services. A well-developed market ecosystem can help lower barriers to use, thereby expanding the application's coverage.

(4) **Socio-cultural and Environmental Context.** Differences across countries and regions in technology acceptance, language environment, perceptions of data privacy, and regulatory policies may lead the same AI application to exhibit markedly different levels of popularity across markets [8].

(5) **Network Effects and Community Influence.** Users' recommendation behaviors [9], exposure through social media, and the dissemination of evaluations and use cases within professional communities can often generate positive feedback loops, accelerating the diffusion of AI applications within user groups.

Together, these five dimensions provide a structured characterization of the comprehensive features of AI applications from technological, functional, market, and social-environmental perspectives. Based on this multidimensional indicator system, the entropy-weighted TOPSIS method [10] is subsequently applied to evaluate and rank the overall performance of AI applications, enabling an analysis of their relative popularity patterns under multiple dimensions.

2.2 Data Sources

The data used in this study are primarily drawn from a user survey conducted by Future Publishing on twelve mainstream artificial intelligence applications. The survey targets technology consumers in the United States and the United Kingdom and provides a systematic overview of representative AI applications currently available in the market, including information on user adoption shares across different markets.

Based on the survey results, this study compiles the adoption shares of each AI application in the US and UK markets and further calculates the average adoption share across the two countries. This averaged measure is used to characterize the relative popularity of AI applications in major English-speaking markets (see Table 1).

Table 1. Survey Results on the Popularity of Artificial Intelligence Applications

Application	Rank	User Share (US)	User Share (UK)	Average User Share	Survey-Based Usage Proportion
DreamStudio	10	10%	7%	8.50%	0.085
Midjourney	10	10%	7%	8.50%	0.085
Stable Diffusion	10	10%	7%	8.50%	0.085
Jasper	9	10%	7%	8.50%	0.09
DALL-E	8	12%	7%	9.50%	0.095
Claude	7	11%	9%	10.00%	0.1
Perplexity	6	12%	9%	10.50%	0.105
Image Creator	5	14%	9%	11.50%	0.115
Grammarly	4	24%	16%	20.00%	0.2
Microsoft Copilot	3	23%	17%	20.00%	0.2
Google Gemini	2	27%	18%	22.50%	0.225
ChatGPT	1	39%	35%	37.00%	0.37

Building on this basis, and to provide a structured characterization of the multidimensional features of AI applications, this study constructs an evaluation index system across five dimensions: technological performance and user experience, functional usefulness and scenario adaptability, market and ecosystem factors, sociocultural and environmental context, and network effects and community influence. The selected indicators are designed to describe the overall performance of AI applications from technological, functional, market, and social-environmental perspectives.

The quantitative scoring of indicators for each dimension is determined based on publicly available industry information and relative comparison methods. Specifically, the assessment draws on a combination of published technical evaluation reports, market research materials, and user feedback, and is further calibrated using expert judgment or user survey results where appropriate. Each indicator is assigned a score on a 1–9 scale [11], with higher values indicating superior relative performance of an application on the corresponding dimension. The resulting scores are reported in Table 2.

Table 2. Multidimensional Factors Influencing AI Application Popularity

Application	Rank by Average User Share	Technological Performance & User Experience	Functional Usefulness & Scenario Fit	Market & Ecosystem Factors	Sociocultural & Environmental Context	Network Effects & Community Influence

ChatGPT	1	9	9	9	8	9
Google Gemini	2	8	8	9	8	8
Microsoft Copilot	3	8	8	9	8	8
Grammarly	4	7	9	8	9	8
Image Creator	5	7	7	8	7	7
Perplexity	6	7	8	7	7	7
Claude	7	8	8	7	7	7
DALL-E	8	8	7	8	7	8
Jasper	9	6	7	7	7	6
DreamStudio	10	7	6	6	6	6
Midjourney	10	9	8	7	7	9
Stable Diffusion	10	8	7	6	6	8

It should be emphasized that the multidimensional indicator scores constructed in this study are not intended for statistical inference on individual variables. Rather, they are designed to support a composite evaluation of the overall characteristics of AI applications across multiple dimensions. Given the limited sample size and the study's focus on relative differences among applications, these indicators provide the foundational input for the subsequent application of the entropy-weighted TOPSIS method to evaluate and rank AI applications.

3.Comprehensive Evaluation and Empirical Analysis of AI Application Popularity

Based on the multidimensional evaluation index system developed in the previous section, this study applies the entropy-weighted TOPSIS method to evaluate and rank the overall performance of twelve mainstream AI applications, with the aim of characterizing their relative popularity under multiple dimensions. By integrating objective weighting with an ideal-solution approach, the entropy-weighted TOPSIS method is well suited for distinguishing the comprehensive performance of evaluation objects in contexts characterized by limited sample sizes and multiple indicators.

Specifically, all evaluation indicators are first transformed to ensure consistent directionality and normalized to eliminate the influence of differences in measurement units and value ranges across indicators. Subsequently, the entropy method [12] is employed to calculate the information entropy of each indicator and to determine the corresponding weights. Under the entropy-weighting scheme, indicators with greater dispersion contain more information and therefore exert a larger influence on the composite evaluation results. This procedure helps reduce the arbitrariness associated with subjective weighting to a certain extent.

After determining the indicator weights, the TOPSIS method [13] is further applied to construct the positive ideal solution and the negative ideal solution. The weighted Euclidean distances between each AI application and the positive and negative ideal solutions are then calculated to measure their relative proximity. The relative closeness coefficient is defined as

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where D_i^+ and D_i^- denote the distances from the positive and negative ideal solutions, respectively. The relative closeness coefficient C_i serves as the composite evaluation index for ranking AI applications. A higher value of C_i indicates that an application's overall performance under the multidimensional indicator system is closer to the ideal state, and thus reflects a higher level of relative popularity.

The adoption of the entropy-weighted TOPSIS method in this study is intended to facilitate a relative evaluation and ranking of AI applications' comprehensive performance [14], rather than to conduct statistical inference on causal relationships between individual factors and application popularity. In a research setting characterized by a limited number of observations and highly correlated multidimensional features, composite evaluation methods are more effective than conventional regression models in revealing overall differences across AI applications.

Based on the above methodology, the next section presents a detailed analysis of the entropy-weighting results and the TOPSIS composite rankings. These findings are further discussed in conjunction with observed user adoption shares to provide an integrated interpretation of the relative popularity patterns of different AI applications.

3.1 Entropy-Weighted TOPSIS Results

Table 3. Weights of Multidimensional Evaluation Factors

Dimension	**Information Entropy (e)**	**Degree of Diversification (d)**	**Weight (%)**
Technological Performance&User Experience	0.933	0.067	14.548
Network Effects & Community Influence	0.899	0.101	22.193
Sociocultural & Environmental Context	0.89	0.11	24.096
Market & Ecosystem Factors	0.887	0.113	24.616
Functional Usefulness & Scenario Fit	0.933	0.067	14.548

The results of the entropy-based weighting procedure are reported in Table 3. As shown in the table, the information contribution of different evaluation dimensions varies across the sample. Among them, **market and ecosystem factors** (24.616%) and **sociocultural and environmental context** (24.096%) receive relatively higher weights, indicating that these dimensions contain greater informational content for differentiating the overall performance of AI applications in the sample. In contrast, **technological performance and user experience** as well as **functional usefulness and scenario fit** are assigned relatively lower weights (both 14.548%), suggesting that the distributions of these indicators are more concentrated across applications and thus play a more limited role in distinguishing composite performance.

It should be emphasized that these weights reflect the *relative discriminating power* of each dimension within the current sample, rather than the magnitude of their causal influence on AI application popularity.

Table 4. TOPSIS Composite Scores and Rankings of AI Applications

AI Application	**Distance to Positive Ideal Solution (D^+)**	**Distance to Negative Ideal Solution (D^-)**	**Composite Closeness Coefficient (C_i)**	**Rank**
ChatGPT	0.16362416	0.9306641	0.85047435	1
Google Gemini	0.28941331	0.76236454	0.72483419	2
Microsoft Copilot	0.28941331	0.76236454	0.72483419	2
Grammarly	0.34156535	0.78143293	0.69584517	3
Image Creator	0.60198945	0.43950456	0.42199433	7
Perplexity	0.62924675	0.39950479	0.38833943	8
Claude	0.58945611	0.45617655	0.43626846	6
DALL-E	0.48981902	0.56181214	0.53422926	5
Jasper	0.80533149	0.26511929	0.2476707	10
DreamStudio	0.95873791	0.12713899	0.11708416	11
Midjourney	0.48234841	0.69727115	0.59109833	4
Stable Diffusion	0.76980218	0.42362225	0.35496362	9

From the TOPSIS composite evaluation results, different types of AI applications exhibit clear structural differences in both composite scores and rankings. **ChatGPT** ranks first with a composite closeness coefficient of 0.85, characterized by a relatively large distance from the negative ideal solution and a small distance to the positive ideal solution. This indicates that, under the constructed multidimensional evaluation framework, ChatGPT's overall performance is closer to the ideal state. **Google Gemini** and **Microsoft Copilot** achieve very similar composite scores and form a second tier, suggesting relatively balanced performance across technological capabilities, market ecosystems, and application scenarios. **Grammarly** ranks third, reflecting its stable performance in specific usage contexts.

From the perspective of application types, **text-based AI applications** generally rank higher, whereas **image-generation applications** display a more dispersed distribution of composite scores. Image-generation tools represented by **Midjourney** perform strongly in certain dimensions, yet still lag behind leading text-based applications in the overall multidimensional evaluation. Other image-generation or vertically specialized applications receive comparatively lower composite scores, indicating that a unified advantage structure across multiple dimensions has not yet emerged for these application types.

Overall, the TOPSIS results reveal the relative performance landscape of current AI applications under multiple dimensions, highlighting a degree of differentiation across application types. These findings provide a foundation for subsequent analysis that integrates observed user adoption shares to further examine the real-world popularity of AI applications.

3.2 Comparison Between Composite Evaluation Results and Observed User Adoption Shares

To assess the practical reference value of the entropy-weighted TOPSIS composite evaluation results [15] in real-world settings, this study further conducts a comparative analysis by aligning the composite ranking outcomes with the average observed user adoption shares of AI applications in the UK and US markets. By placing the evaluation-based rankings side by side with actual usage shares, the comparison allows for a straightforward and intuitive examination of whether the multidimensional evaluation results display a similar pattern to the applications' real-market popularity. In other words, the purpose of this section is to observe the extent to which the ranking implied by the composite scores corresponds to the relative popularity reflected in observed adoption levels.

Overall, AI applications that are ranked near the top in the composite evaluation tend to show relatively high user adoption shares in practice. Representative applications such as ChatGPT, Google Gemini, and Microsoft Copilot are positioned among the leading performers in the TOPSIS-based ranking, and they also exhibit comparatively high levels of user adoption share across the UK and US markets. This parallel pattern indicates that the multidimensional composite evaluation and the real-world popularity measure are, in general, moving in the same direction. Put differently, the applications that perform well in the composite assessment also tend to be those that are more widely used by consumers in the observed markets, suggesting a broadly consistent trend between evaluation outcomes and actual popularity.

At the same time, it is also evident that for some AI applications, the composite ranking and the observed adoption share do not fully coincide, and a certain degree of divergence can be identified. For example, some applications that score relatively well in the composite evaluation have not yet reached adoption shares that fully match their overall performance levels as implied by the composite scores. Such a gap may be associated with factors already present in the market context, including the pace at which the application is promoted, the extent of user awareness and recognition, or the length of time the application has been available and penetrating the market. Conversely, there are also cases where applications show relatively high adoption shares while achieving only moderate composite evaluation scores. This situation may reflect the advantages derived from an established user base or from the strength of a platform ecosystem in which the application is embedded. These patterns collectively suggest that real-world popularity is not determined solely by multidimensional characteristics captured in the evaluation framework, but may also be influenced by market-stage and transitional factors that vary across applications.

In summary, the comparison reveals that a certain degree of consistency exists between the composite evaluation results and the observed user adoption shares, while structural deviations are also present. The above juxtaposition indicates that the entropy-weighted TOPSIS method can provide a meaningful reference for describing the multidimensional overall performance of AI applications. Nevertheless, the interpretation of its ranking outcomes still needs to be combined with specific market environments and the particular stage of development at which an application is positioned, so as to better understand why alignment is strong in some cases and less complete in others.

4. Conclusion

This paper addresses the question of why the popularity of AI applications differs across the UK and US markets by developing a multidimensional evaluation and comparison framework. Rather than treating "popularity" as a single-dimensional outcome, the study conceptualizes it as a composite phenomenon shaped by multiple attributes that jointly influence users' adoption and continued use. Accordingly, the proposed indicator system is constructed along five dimensions that are closely aligned with how AI applications are experienced and evaluated in practice: technological performance and user experience, functional usefulness and scenario adaptability, market and ecosystem factors, sociocultural and environmental context, and network effects. These dimensions are intended to capture, in a structured way, the diverse features that may contribute to applications becoming more widely used and more "popular" relative to other competing tools.

Based on this multidimensional framework, the study employs the entropy-weighted TOPSIS method to conduct a comprehensive evaluation and ranking of twelve mainstream AI applications. The use of entropy weighting helps to determine indicator weights in a more data-driven manner, and the TOPSIS procedure synthesizes performance across indicators to generate an overall ranking. This methodological choice is particularly suitable for the research setting of this paper, which is characterized by a relatively limited number of evaluated applications but a heterogeneous set of features that must be considered simultaneously. Under such conditions, the analysis serves an exploratory purpose: it provides a systematic description of relative performance patterns across applications and offers an organized way to compare their comprehensive profiles when multiple criteria are relevant and potentially non-commensurable.

The evaluation results reveal clear differentiation in the composite performance of AI applications across the five dimensions. Text-based applications represented by ChatGPT, Google Gemini, and Microsoft Copilot consistently rank higher in the composite evaluation. Their leading positions reflect a more balanced advantage structure when assessed across the multidimensional indicators. In particular, these applications appear to maintain relatively consistent strengths across aspects such as broad applicability across common usage scenarios, more mature market ecosystem support, and stronger levels of user acceptance. In other words, their higher composite rankings do not result from an isolated advantage in a single dimension, but rather from relatively robust performance across several key dimensions at the same time. This pattern is consistent with the observation that applications achieving higher popularity often display a more comprehensive set of strengths that support both initial adoption and continued usage.

By contrast, image-generation applications show a more dispersed distribution of composite scores. While some image-generation tools exhibit notable performance in particular technological aspects, their overall composite results vary more widely across the evaluated set. The evaluation suggests that, within this segment, strong performance in one or several specific dimensions has not yet translated into a stable and comprehensive advantage structure at the multidimensional level. As reflected by the dispersion of composite scores, image-generation applications appear to differ more substantially from one another in their overall profiles, and the segment as a whole does not display the same degree of consistently high composite performance observed among the leading text-based applications. In the context of this study, such a pattern is interpreted as reflecting differences in the degree of maturity across application segments when evaluated from multiple criteria simultaneously.

To further assess the practical relevance of the composite evaluation outcomes, the paper conducts an additional comparison between the entropy-weighted TOPSIS rankings and observed usage data. Specifically, the study juxtaposes the composite evaluation results with the average user adoption shares of AI applications in the UK and US markets. This step is important because it allows the analysis to examine whether the multidimensional evaluation outcomes align with a direct behavioral indicator of real-world popularity—namely, the relative extent to which applications are actually used by users in the market. By comparing the evaluation ranking with observed adoption shares, the paper provides an intuitive assessment of the degree of consistency between the framework-based composite results and market-based popularity as reflected in usage patterns.

The comparison indicates that, in overall terms, there is a relatively high degree of consistency between the composite evaluation outcomes and observed adoption shares. Applications that rank higher in the composite evaluation tend, in general, to display higher user adoption shares in the UK and US markets. This alignment suggests that the proposed multidimensional evaluation framework is, to some extent, capable of capturing real-world popularity patterns among AI applications, at least in terms of broad ranking tendencies. At the same time, the analysis also finds that deviations between composite rankings and actual usage remain for some applications. In certain cases, applications with relatively strong composite evaluation performance have not yet achieved adoption shares that fully match their composite scores. Such differences may relate to factors associated with the market context, including the pace and intensity of application promotion, the degree of user awareness or recognition, and the length of time an application has been present in the market. Conversely, some applications may show relatively high adoption shares despite achieving only moderate composite scores, potentially reflecting advantages related to an existing user base or the strength of a supporting platform ecosystem. These observed deviations imply that, beyond multidimensional characteristics summarized in the evaluation framework, market-stage and external factors may also shape the realized popularity of AI applications in practice.

Overall, the findings of this study suggest that the popularity of AI applications is best understood as the outcome of the joint influence of multiple dimensions, rather than being adequately represented by any single indicator. Compared with single-indicator approaches, the entropy-weighted TOPSIS–based composite evaluation provides a more comprehensive perspective for describing and comparing the relative market positions of AI applications across the UK and US contexts. It is important to emphasize, however, that the objective of this study is to describe relative performance and popularity patterns through a multidimensional composite evaluation, rather than to infer causal mechanisms that determine popularity. Given constraints related to sample size and data availability, future research may expand the scope of applications and datasets, and further combine this evaluation perspective with econometric methods, in order to investigate more deeply the mechanisms underlying the formation of AI application popularity.

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