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Revisiting delayed recognition in science: A large-scale and comprehensive study

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Abstract
Delayed recognition, exemplified by the phenomenon of sleeping beauties, presents a compelling narrative within the dynamics of scientific impact and innovation. Our investigation delves into the nuanced facets of delayed acknowledgement, uncovering its profound implications and innovation pathways. Through the analysis of extensive datasets and advanced methodologies, we elucidate the intricate connections between delayed recognition and the realms of scientific and technological influence. Our study not only reveals correlations between atypical combinations of knowledge and the emergence of sleeping beauties but also sheds light on the relationship between delayed recognition and disruptive paradigm shifts in scientific evolution, suggesting their potential role in shaping scientific breakthroughs. Furthermore, our analysis highlights the journey of delayed recognition, often culminating in significant contributions across diverse fields, including notable achievements, such as Nobel-worthy milestones. This article advances our understanding of scientific evolution and the complex landscape of acknowledging pioneering research.

Keywords
Delayed recognition; disruption; science of science; sleeping beauty; Nobel prize; novelty

1. Introduction

The progression of human advancement intricately aligns with the unfolding of scientific discoveries. Innovative and paradigm-shifting inquiries across diverse domains have been pivotal in propelling progress [1–3]. However, the acknowledgement of pioneering research does not always occur immediately. Some significant scientific works garner widespread attention and citations only after a substantial period from their initial introduction [4]. This intriguing phenomenon, referred to as temporally deferred acknowledgement in scientific discourse [5], often termed a 'sleeping beauty' by van Raan [6], offers an unconventional perspective on scientific impact and citation dynamics.

Temporal deferment emerges when a scientific manuscript receives limited attention on its release [7] but gains significant recognition and citations later on [8]. Investigating dormant intellectual works sheds light on the intricate dynamics of scientific exploration [9], unveiling the multifaceted elements shaping the acknowledgement of scientific achievements [10,11]. Such articles, characterised by delayed acknowledgement, often display extended periods of limited

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attention followed by sudden bursts of recognition, resulting in postponed acknowledgement and evaluation of their impact. This temporal gap delineates the interval between publication and the point at which the scientific community assimilates the revelation [12]. Consequently, examining delayed recognition in science holds significant implications for advancing scientific research and understanding [13,14].

The intriguing phenomenon of delayed recognition, characterised by an initial lack of citations, reveals a compelling pattern where scholarly articles, once emerging from obscurity, amass significant scientific influence over an extended duration [10,15]. This trajectory of inquiry prompts the fundamental question of whether these 'sleeping beauties' ultimately ascend to become established as milestones or scientific breakthroughs [16]. Current research uncovers that milestone papers, akin to those esteemed as Nobel prize-worthy, often undergo considerable time lapses before gaining acknowledgement [17]. This delayed recognition stems from the nuanced nature of scientific breakthroughs, which may not immediately demonstrate noticeable impact but rather require a period of maturation [18,19].

Another intriguing aspect revolves around the inherent innovativeness intrinsic to papers that experience delayed recognition [20,21]. This phenomenon can be attributed to the inherent progression of scientific knowledge. Breakthroughs often occur incrementally, with each new discovery building on previous findings [22]. Notable roles, such as 'precocious discoveries' and 'transformative innovations' [23], have been associated with instances of delayed recognition, often intertwined with heightened levels of disruptive innovation [24]. This intricate interplay highlights the dynamic nature of scientific evolution, wherein delayed recognition stands as a testament to the intricate journey of knowledge discovery and dissemination [25].

While existing scholarly work has provided valuable insights into the complex nature of deferred recognition in the scientific realm, notable gaps and contentious points persist. The multifaceted nature of science, spanning diverse temporal and disciplinary domains, along with the complexities involved in evaluating scientific and technological impact, and the integration of critical concepts, such as innovation, has led to ongoing discussions [26]. Addressing these issues requires extensive datasets and advanced methodological frameworks [27]. In this study, we aim to tackle this pressing need by assembling a comprehensive dataset and creating diverse metrics to thoroughly assess the scientific and commercial implications [28,29] of research endeavours. Notably, we introduce the concepts of novelty [30] and disruption [31] as crucial indicators of the inherent innovativeness in scientific inquiries. Furthermore, we analyse both highly impactful papers and those acknowledged by the esteemed Nobel Prize [32]. This approach sheds light on discernible trends that underscore the establishment of fundamental knowledge paradigms and significant milestones in the scientific field.

Building on preceding discussions, this article systematically explores several research inquiries:

(**RQ1**) What intricate connections exist between delayed recognition and the scientific and technological impact of research?
(**RQ2**) Do sleeping beauties demonstrate a higher likelihood of becoming significant hits or Nobel-winning milestones?
(**RQ3**) To what extent is there a relationship between delayed recognition and the levels of disruption and novelty in science?
(**RQ4**) How does the phenomenon of sleeping beauties manifest differently across various fields of study?

The primary aim of this article is to comprehensively investigate the intriguing phenomenon of delayed recognition in science. By addressing these research questions, our goal is to uncover the intricate dynamics behind scholarly articles that initially receive limited attention but later gain substantial impact. Through a detailed analysis encompassing scientific and commercial influence, and factors such as disruption and novelty, we aim to shed light on the mechanisms driving the emergence of sleeping beauties in scientific literature. In addition, our investigation extends to determining the likelihood of these latent gems achieving canonical status and their role in shaping crucial milestones across diverse disciplines. By adopting a multidimensional approach, this study contributes to a deeper comprehension of the evolving nature of scientific impact and the complexities involved in acknowledging groundbreaking research.

2. Literature review

2.1. Identify delayed recognition in science

Delayed recognition in scientific literature characterises papers that receive minimal citations or acknowledgement within the immediate years following their initial publication but subsequently gain traction and recognition over an extended period [5,33]. This phenomenon underscores the temporal gap between the dissemination of research findings and their substantive impact on the scientific community. Studies exploring this phenomenon also refer to terms, such as 'Resisted

Discoveries' [34], 'Late-bloomers' [35] and the 'Mendel Syndrome' [36]. Presently, these papers are commonly known as 'Sleeping Beauties' [6] – publications that remain unnoticed for an extended period and then suddenly attract significant attention in terms of citations. This trajectory deviates from the conventional citation pattern and is identified as one of the seven myths in bibliometrics [8], underscoring its importance in the realm of science.

Van Raan [6] initially delved into the concept of delayed recognition in papers and proposed three criteria – depth of sleep, length of sleep and awakening intensity – as markers to identify sleeping beauties. Subsequently, scholars extensively studied this phenomenon, recognising that detecting sleeping beauties can unveil transformative research and provide insights into a paper's impact from a dynamic trajectory perspective [37]. Van Raan's quantitative standards, along with the measures proposed by Ke et al. [38], facilitated large-scale quantitative research on sleeping beauties, elucidating their unique role in knowledge diffusion and emphasising the necessity of considering their existence from the perspective of citation trajectories.

Quantitative criteria for studying delayed recognition can be categorised into three types: average-based, quartile-based and parameter-free. For instance, van Raan [6] introduced an average-based criterion defining a sleeping beauty as a publication that remains unnoticed for an extended period before experiencing a sudden surge in attention. Conversely, Costas et al. [39] proposed a quartile-based measure, identifying delayed recognition by pinpointing the year when an article receives at least 50% of its citations for the first time. However, these approaches may pose computational burdens or encounter precision limitations [37].

Ke et al. [38] introduced a parameter-free index known as the Beauty coefficient. This metric quantifies a paper's status as a sleeping beauty by evaluating the differences between its citation trajectory and a reference line drawn from the publication year to the year of maximum citations. For comprehensive analyses, the parameter-free measure stands out as it avoids subjective biases and arbitrary thresholds, offering a more objective assessment of delayed recognition [1].

2.2. Impact and innovation of sleeping beauties

The concepts of delayed recognition and the sleeping beauty effect may signify shifts in research paradigms [6] or societal acknowledgement, as observed in Nobel Prize recognition [40]. Van Raan's [14] recent analysis delves into the dynamic citation patterns of sleeping beauties, revealing crucial turning points in their citation trajectories, often occurring considerably later. Assessing the scientific impact of sleeping beauties presents challenges [3], particularly when considering lengthy citation windows due to the unique trajectories of these papers.

Beyond scientific impact gauged by citation counts, scholars are increasingly recognising the technological impact of these dormant papers [41]. Identifying sleeping beauty papers within a field and assessing their total number of patent citations demonstrate that such papers often attract more citations from patents, highlighting their substantial knowledge contribution to patents and warranting further investigation.

The bias against novelty in science [4,42], where novelty indicates unconventional combinations of existing knowledge [30], suggests that novel papers might initially receive few citations but may gain recognition for their novelty in the long run. The concept of delayed recognition is closely linked to disruption in science. Wu et al. [19] found that disruptive papers are more probably to evolve into sleeping beauties. Existing research suggests that milestone papers, comparable to those deserving Nobel Prize recognition, often undergo prolonged periods before being acknowledged [17,43]. This delay is attributed to the intricate nature of scientific breakthroughs, which might not immediately demonstrate significant impact but require a maturation phase [18,44]. Miura et al. [10] noted that slowly cited papers often originate from small teams, disrupt established knowledge, introduce fairly novel insights and gradually disseminate across broader fields.

However, many studies on the impact of sleeping beauties primarily focus on small sample datasets within specific fields [45]. These studies often lack state-of-the-art metrics, such as the disruption and novelty index [27,46], potentially limiting a comprehensive understanding of the scope and implications of these influential yet dormant papers.

3. Data and method

3.1. Data

This study relies on two extensive datasets: the Microsoft Academic Graph (MAG) and the recently introduced SciSciNet [47]. The MAG is a leading bibliometric repository of scholarly research, renowned for its comprehensive coverage [48]. The SciSciNet dataset [47] is built on an identical version of the MAG dataset used in our study, enhancing it by providing additional information for each paper, including links to publicly accessible resources. Together,

these datasets serve as invaluable sources of citation data, allowing us to investigate the inherent attributes and patterns associated with delayed recognition in scientific research.

To ensure a suitable timeframe for scrutinising citations relevant to our investigation of delayed recognition in science [49], our study focuses specifically on journal papers published from 1900 to 2000. We do not impose a fixed citation window as our primary aim is to study delayed recognition. All papers in our citation network have at least a 20-year citation window, and citations are tracked until 2021. Our analysis centres on research papers that accumulate citation counts exceeding 50, aligning with the citation trajectories used to identify instances of delayed citation with parameter-free methods. As a result, our analytical efforts are based on a corpus of 2,406,358 research papers.

In our framework, 'hit papers' are defined as the top 1% highly cited papers (total citations) in their respective year and field [50]. Similarly, the cohort of milestones comprises Nobel-winning papers in Natural Science fields. Hit papers are identified using data from the expansive MAG dataset covering 19 distinct fields. Nobel-winning papers in Physics, Chemistry and Medicine are curated from meticulous work by Li et al. [32]. This amalgamation results in a corpus of 489 milestone papers, including 159 Nobel-winning papers in Physics, 143 in Chemistry and 187 in Medicine.

3.2. Quantify delayed recognition

To quantify delayed recognition in science, various methodologies have been proposed, including citation curve fitting and setting arbitrary thresholds [51,52]. However, these approaches can be computationally complex or constrained by precision limitations [37]. To overcome these challenges and enable a comprehensive large-scale analysis, we employ a parameter-independent metric known as the beauty coefficient (B) [38]. This metric serves as a quantifiable measure of dormant yet influential research, assessing the impact of scientific papers based on their citation trajectory.

The beauty coefficient (B) is computed through a systematic comparison of a paper's citation trajectory to a reference line that considers its publication year, the peak annual citation count and the year of this peak attainment. This offers an illuminating measure of deferred acknowledgement. As depicted in Figure 1(a), the reference line $L_t = \frac{c_{t_m}-c_0}{t_m}t + c_0$ is a straight line that connects the points $(0, c_0)$ and (t_m, c_{t_m}) in the time-citation plane, where c_t is the number of citations received in the t^{th} year after publication, t is the age of the paper and t_m is the year when the paper receives its maximum number of yearly citations. The beauty coefficient formula involves computing the ratio between $L_t - c_t$ and $max(1,\ c_t)$ for each $t \leqslant t_m$

$$B = \sum_{t=0}^{t_m} \frac{\frac{c_{t_m}-c_0}{t_m}t + c_0 - c_t}{max\{1, c_t\}} \tag{1}$$

where L_t is the equation of the reference line at time t, and then summing up the ratios from $t = 0$ to $t = t_m$. The denominator $max(1,\ c_t)$ penalises early citations, so the later those citations are accumulated, the higher the value of B. B is zero for papers with $t_m = 0$, negative for papers with a concave citation trajectory, and increases with both the length of the sleeping period and the awakening intensity.

Overall, the beauty coefficient provides a precise and parameter-free measure of the sleeping beauty, which can be computed for any paper and takes into account the entire citation history. Furthermore, the awakening time, t_α, is the year when the distance d_t reaches its maximum, where t is less than t_m. The distance d_t is defined as $d_t = \frac{|(c_{t_m} - c_0)t - t_m c_t + t_m c_0|}{\sqrt{(ctm - c0)^2 + t_m^2}}$, and the awakening time t_α is encapsulated by the expression

$$t_\alpha = arg\{max_{t<t_m} d_t\} \tag{2}$$

According to van Raan's definition and previous studies on citation patterns of sleeping beauties [6,14], a notable turning point around the awakening time in citation trajectories signifies significantly high values of the beauty coefficient (B). To exemplify this, we narrow our focus to papers published in 1950 within our dataset and plot their yearly citation trajectories until 2021, covering a span of 71 years (as depicted in Figure 1). Figure 1(b) highlights the top five papers exhibiting the highest B values, surpassing 1641, and awakening times (t_α) exceeding 47 years. For instance, the paper titled 'Index for rating diagnostic tests' [53], published in the journal *Cancer*, introduced the Youden Index. Despite its status as a widely recognised measure for evaluating the clinical diagnostic ability of a test using the receiver operating characteristic curve (ROC) curve, this paper received limited attention until 2007, with an awakening time (t_α) of 57.

A deeper understanding emerges from comparing the citation trajectories of papers within the top 5% of B values in 1950 ($B > 266.4$) against other papers, as depicted in Figure 1(c) and (d), respectively. A substantial divergence in

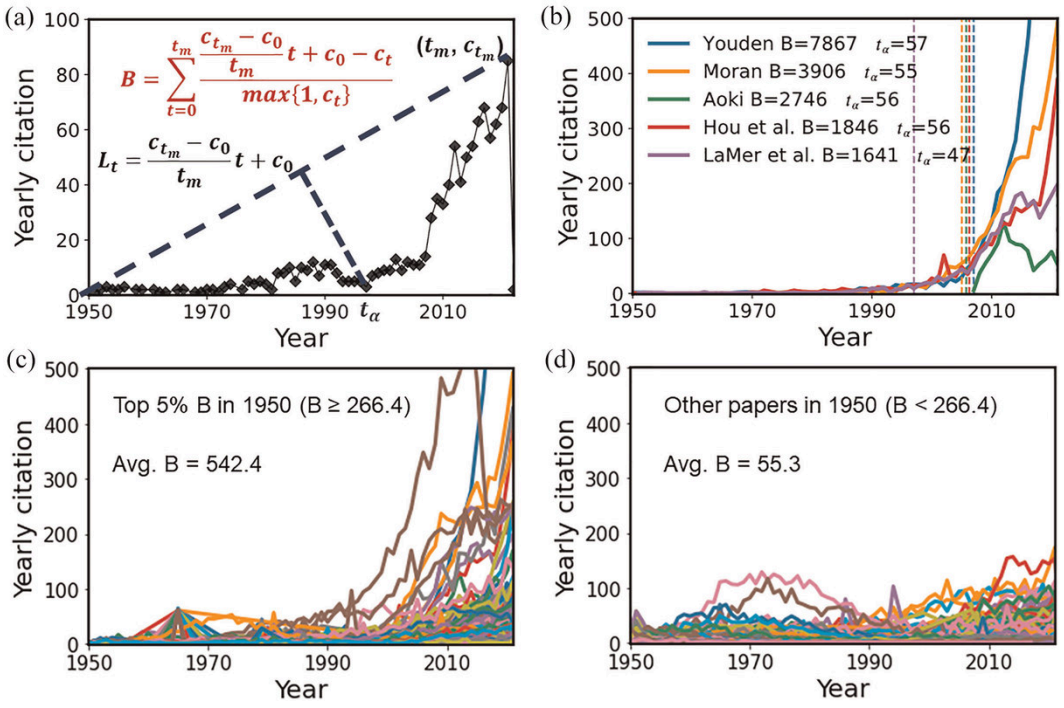


Figure 1. Quantifying delayed recognition in science: (a) visualisation of delayed recognition, defining B (beauty coefficient) and t_α (awakening time), (b) the citation trajectories of papers the top five papers exhibiting the highest B values, (c) the citation trajectories of papers within the top 5% of B values in 1950 ($B \geqslant 266.4$) and (d) the citation trajectories of other papers in 1950 ($B < 266.4$).

citation patterns is evident: sleeping beauties suddenly attract attention post the awakening time, while others exhibit either linear or decreasing citation curves over time. This contrast accentuates the distinct citation behaviours between papers experiencing delayed recognition and those following more conventional citation trajectories.

3.3. Metrics and models

3.3.1. Impact variables. In the pursuit of gauging the scientific and commercial ramifications inherent within scientific research endeavours, we deploy two distinct variables to provide comprehensive insights:

(1) **Scientific impact**: We measure scientific impact primarily through citation counts, recognised as a fundamental metric for evaluating the academic influence of scholarly works [54]. Using the citation network within MAG, we compute aggregate citation counts. However, accounting for the heterogeneity across different years and citation windows poses challenges. To address this complexity, we aim to mitigate variance through the application of year fixed-effect models.
(2) **Technological impact**: The quantification of technological impact revolves around the number of citations of papers by patents [28]. These connections between papers and patents provide deep insights into the technological implications arising from scientific inquiry [55]. Assessing how research findings are applied in practical contexts underscores the pivotal role of research in driving technological progress.

3.3.2. Innovation variables. Our approach to gauge the level of innovation of papers encompasses two distinct variables:

(1) **Disruption**: Drawing on the theoretical framework of the disruption in science [18,19,31], we leverage the Disruption index to offer a quantitative assessment of the degree of disruption, defined as

$$Disruption\ index = \frac{n_{DC} - n_{CC}}{n_{DC} + n_{CC} + n_{RC}} \quad (3)$$

encompasses the components of CC, symbolising the count of publications citing the focal paper (FP) along with its referenced works, DC representing the count of publications citing FP without referencing its cited sources, and RC signifying the count of publications citing FP's references without citing FP itself. The Disruption index synthesises these intricate citation dynamics to elucidate the extent of disruption inherent within a given paper's impact. As exemplified in Figure S1, a lower Disruption value implies that the focal paper references sources that are also cited by a considerable multitude of papers referencing FP. This signals the convergence with established paradigms, as the focal paper aligns with and fortifies existing knowledge structures. Conversely, higher Disruption values connote papers of profound disruptive nature, denoting contributions that redefine paradigms and usher in transformative shifts [44]. In contrast, lower values are indicative of papers reinforcing the prevailing research paradigms within their respective domains. Through the instrumentality of the Disruption index, a profound illumination is cast on the patterns governing knowledge dissemination, paradigm shifts and the intricate tapestry of innovation within scientific domains [56].

(2) **Novelty**: Novelty is discerned as the manifestation of atypical combinations of knowledge [30,57,58]. Our operationalisation of this metric involves a meticulous scrutiny of the distribution of journal pairs present within a paper's reference list. Each journal pairing is transformed into z-scores, serving as standardised representations. To quantify Novelty, we engage in Monte Carlo simulations [59], creating reshuffled networks through random edge reassignment while preserving the temporal and distributional attributes of the original citation network. Distinct papers exhibit unique distributions of journal pairings, with certain pairings displaying variations in prevalence compared to chance expectations. The computation of Novelty for each journal pair is encapsulated by the expression

$$Novelty_{i,j} = \frac{obs(pair_{ij}) - exp(pair_{ij})}{\sigma(pair_{ij})} \quad (4)$$

where $obs(pair_{ij})$ signifies the observed frequency of the journal pair in the actual dataset, $exp(pair_{ij})$ represents the mean and $\sigma(pair_{ij})$ denotes the standard deviation of journal pairs obtained from 10 randomised simulations of the reshuffled network. To encapsulate the information within the distribution, denoted as a set $\{NoveltyU_{i,j} \mid i,j \in J\}$, wherein J encompasses all journals within the reference list, we leverage the negative value of the 10th percentile of the Novelty set as a succinct summary statistic [30]. The rationale behind adopting the negative value lies in the fact that elevated z-scores correlate with diminished Novelty (as depicted in Figure S1). The final variable is then transformed into percentile values (ranging from 1 to 100). Through this variable, we are poised to quantitatively evaluate the extent of Novelty characterising each paper within our study, thereby facilitating insights into the fusion of distinct knowledge domains within scholarly publications.

3.3.3. Control variables. In recognition of the imperative to counteract potential confounding factors that might exert influence on the target outcomes, a strategic inclusion of several control variables is implemented within our analytical framework.

Within our analytical framework, we acknowledge the necessity of mitigating potential confounding factors that might influence our target outcomes. To address this, we integrate several control variables strategically. First, the number of references within a paper serves as a proxy for the breadth and depth of literature incorporated into the research, offering insights into the comprehensiveness of scholarly foundations. Second, the team size, indicated by the number of authors, stands as a nuanced indicator of the scale of the research team involved in the scientific inquiry. In addition, we consider international collaborations [60], recognising their global reach and potential impact. Third, funding information is included as a control variable to account for financial support's potential influence on research outcomes. Fourth, we incorporate the age and publication count of authors before the paper's publication to gauge the authors' experience and academic standing [61], providing insights into their scholarly impact and productivity, factors that could influence overall research impact.

Moreover, to address potential heterogeneity across scientific fields, journals and temporal variations, our regression models integrate three-level fixed effects[62]. First, first-level fields in the MAG dataset are employed to control for disparities among diverse scientific domains, acknowledging variations in research impact and innovation across disciplines. Second, journal fixed effects are incorporated to account for variations associated with publication outlets, encompassing a wide array of 14,290 distinct journals. Third, year fixed effects are included to capture temporal variations and trends over time, ensuring comprehensive consideration of any changes in impact and innovation across different timeframes

within our analysis. These measures collectively help minimise potential biases and facilitate a more robust assessment of the impact and innovation of scientific research.

4. Results

4.1. Distributions

In our examination of delayed recognition in science, we first delve into the distributions of the beauty coefficient (B) and awakening time (t_α) across various temporal and field dimensions, as depicted in Figure 2 and supplemental Figure S2 available online. While t_α operates as a counting variable, the distribution of B follows a power law distribution (Figure 2(a)). To assess the impact of t_α and B on scientific impact and innovation, we employ log variables and focus solely on papers with B values above or equal to 0 in our regression analysis (section 4.2).

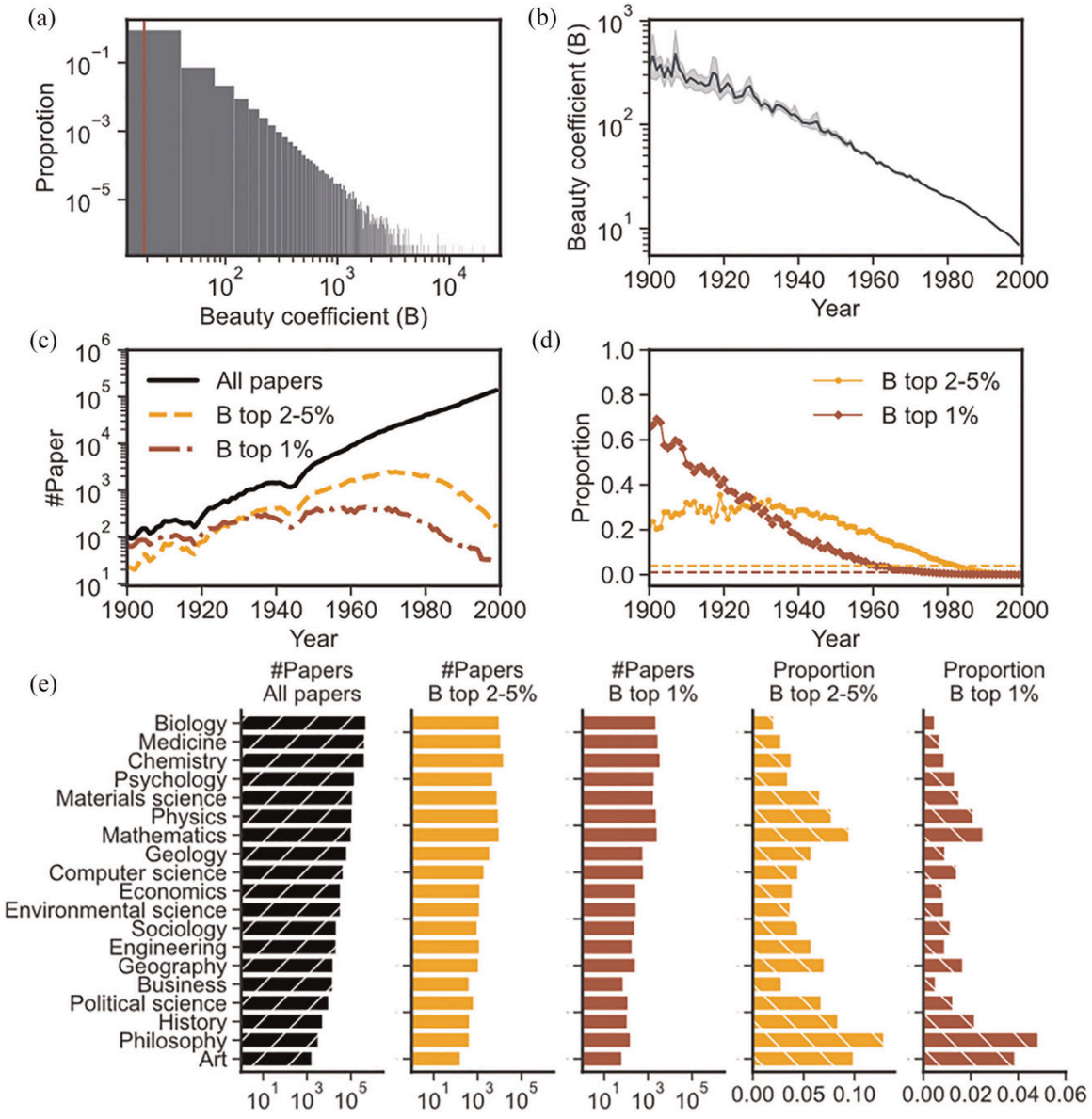


Figure 2. Distribution of *B* (Beauty Coefficient) over time and across fields: (a) the power law distribution of B, where the red line indicates the average B value (18.8), (b) average B values for all papers over year, where shaded areas represent 95% confidence intervals, (c–d) the number and proportion of papers with top 1% *B* (B $\geqslant$ 180.2) and top 2%–5% *B* (B $\geqslant$ 72.5) over year and (e) the number and proportion of papers with top 1% *B* (B $\geqslant$ 180.2) and top 2%–5% *B* (B $\geqslant$ 72.5) across fields.

Given the rarity of sleeping beauties in science, akin to Ke et al.'s approach [38], we identify papers within the top 1% of B and those ranking in the subsequent 2%–5% as the most typical sleeping beauties. The distribution showcased in Figure 2(c)–(e) reveals that while a majority of papers exhibited significant delayed recognition in the 1900s, there has been a decline in the proportion of papers identified as sleeping beauties after 1980.

Furthermore, our exploration uncovers notable disparities in delayed recognition across scientific fields. Fields such as Philosophy and Mathematics exhibit a higher likelihood of experiencing delayed recognition, while Biology and Medicine show a considerably lower probability of being classified as sleeping beauties. These trends hold true when analysing awakening time (t_α) instead of beauty coefficient (B) (Supplemental Figure S2 available online). Collectively, these findings underscore the divergence across timeframes and fields in our analysis of delayed recognition in scientific research, shedding light on distinct temporal and disciplinary patterns associated with this phenomenon.

4.2. Impact, hits and milestones

Addressing RQ1, our comprehensive investigation delves into the intricate relationship between delayed recognition, quantified through the beauty coefficient (B) and awakening time (t_α), and their influence on scientific and technological impact. The results depicted in Table 1 unveil a significant positive correlation between delayed recognition and both scientific and technological impact. Controlling for various confounding factors, a 1% increase in B is associated with a 4.79% rise in citation counts and a 1.36% increase in patent citations. Similarly, a 1% increase in t_α correlates with a 4.79% elevation in citation counts and a substantial 7.35% rise in patent citations. These findings underscore the notable relationship between delayed recognition and heightened scientific and technological impact.

Moreover, our analysis examines the impact of the beauty coefficient (B) and awakening time (t_α) on short-term scientific impact, specifically within 10-year and 5-year citation periods, as outlined in supplemental Table S3 available online. The results reveal a significant negative association between short-term citation impact and delayed recognition. This suggests that sleeping beauties tend to receive lower short-term scientific impact, cautioning against sole reliance on 10-year citations for analysis purposes [63].

It is important to note that the beauty coefficient (B) is derived from the citation trajectory, which might raise endogeneity concerns when analysing its relationship with citation counts and patent citations. However, awakening time (t_α) functions solely as a year variable, presenting a clearer validation of our conclusions: sleeping beauties tend to receive notably increased citations after their awakening period, emphasising the enduring impact of delayed recognition on scientific and technological advancement.

In addressing RQ2, we aim to define distinctive characteristics for hit papers and milestones in science. Figure 3(a) and (b) sheds light on the specific tendencies observed among different paper types in their likelihood of becoming hit papers. A significant finding emerges: papers with prolonged awakening times and higher beauty coefficients are more inclined to become hit papers. The relationship between awakening times and the probability of becoming a hit paper showcases an almost linear trend. However, concerning beauty coefficients, only a small fraction of papers with the highest B values exhibits significantly high hit rates. This rarity of sleeping beauties contributes to their status as treasures within the realm of scientific literature. These findings retain their robustness under stringent control measures and the incorporation of fixed effects, as evidenced by the outcomes presented in Table 2 (Models 1–2). This reinforces the notion that papers characterised by extended periods of delayed recognition and higher beauty coefficients possess an elevated likelihood of attaining the status of hit papers in their respective fields.

Delving into the meticulous examination of milestone achievement across distinct scientific fields – Physics, Chemistry and Medicine – unveils a diverse landscape. Figure 3(c)–(h), complemented by insights from Table 2 (Models 3–8), paints a nuanced narrative. Significantly, prolonged awakening times and higher B values collectively enhance the likelihood of papers attaining milestone status. However, this trend manifests with distinct variations across different fields. Nobel-winning papers in Physics exhibit a pronounced inclination towards the domain of sleeping beauties, often characterised by elongated awakening times (Figure 3(c) and (d)). In contrast, Chemistry and Medicine Nobel-winning papers display a preference for shorter awakening times, with many milestones not falling into the category of sleeping beauties (Figure 3(e)–(h)). Nevertheless, the effects of the beauty coefficient (B) and awakening time (t_α) on milestones are consistently positive and significant across all fields, as demonstrated in Table 2. This underscores the influence of delayed recognition on the attainment of milestone status, albeit with nuanced patterns observed among different scientific disciplines.

Table 1. The relationship between scientific and technological impact and delayed recognition.

Dependent variable	log (citation count)				log (patent citation)			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent variables								
log (B)	0.0433***	0.0479***			0.0233***	0.0271***		
	(0.0004)	(0.0004)			(0.0014)	(0.0014)		
log(t_α)			0.1305***	0.1356***			0.0688***	0.0735***
			(0.0004)	(0.0004)			(0.0018)	(0.0018)
Control variables								
log (ref)		0.0436***		0.0462***		0.0206***		0.0216***
		(0.0004)		(0.0004)		(0.0016)		(0.0015)
log (team size)		−0.0090***		−1.6E-06		0.0793***		0.0829***
		(0.0008)				(0.0030)		(0.0030)
International		0.0042***		0.0031**		−0.0298***		−0.0304***
		(0.0011)		(0.0011)		(0.0043)		(0.0043)
Funding		0.0332***		0.0338***		0.0071		0.0081.
		(0.0016)		(0.0015)		(0.0048)		(0.0048)
log (author age)		0.0150***		0.0073***		−0.0184***		−0.0236***
		(0.0011)		(0.0011)		(0.0046)		(0.0046)
log (author pubs)		0.0296***		0.0352***		0.0087***		0.0120***
		(0.0007)		(0.0007)		(0.0025)		(0.0025)
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,085,780	2,085,780	2,085,780	2,085,780	592,086	592,086	592,086	592,086
R2	0.0896	0.10056	0.1196	0.13176	0.12549	0.12692	0.12739	0.12898

Note: All models use ordinary least square (OLS) regression. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Standard errors are presented in parentheses. Since the patent citation data are missing largely in MAG, especially for old publications, we focus on papers that receive at least one patent citation.

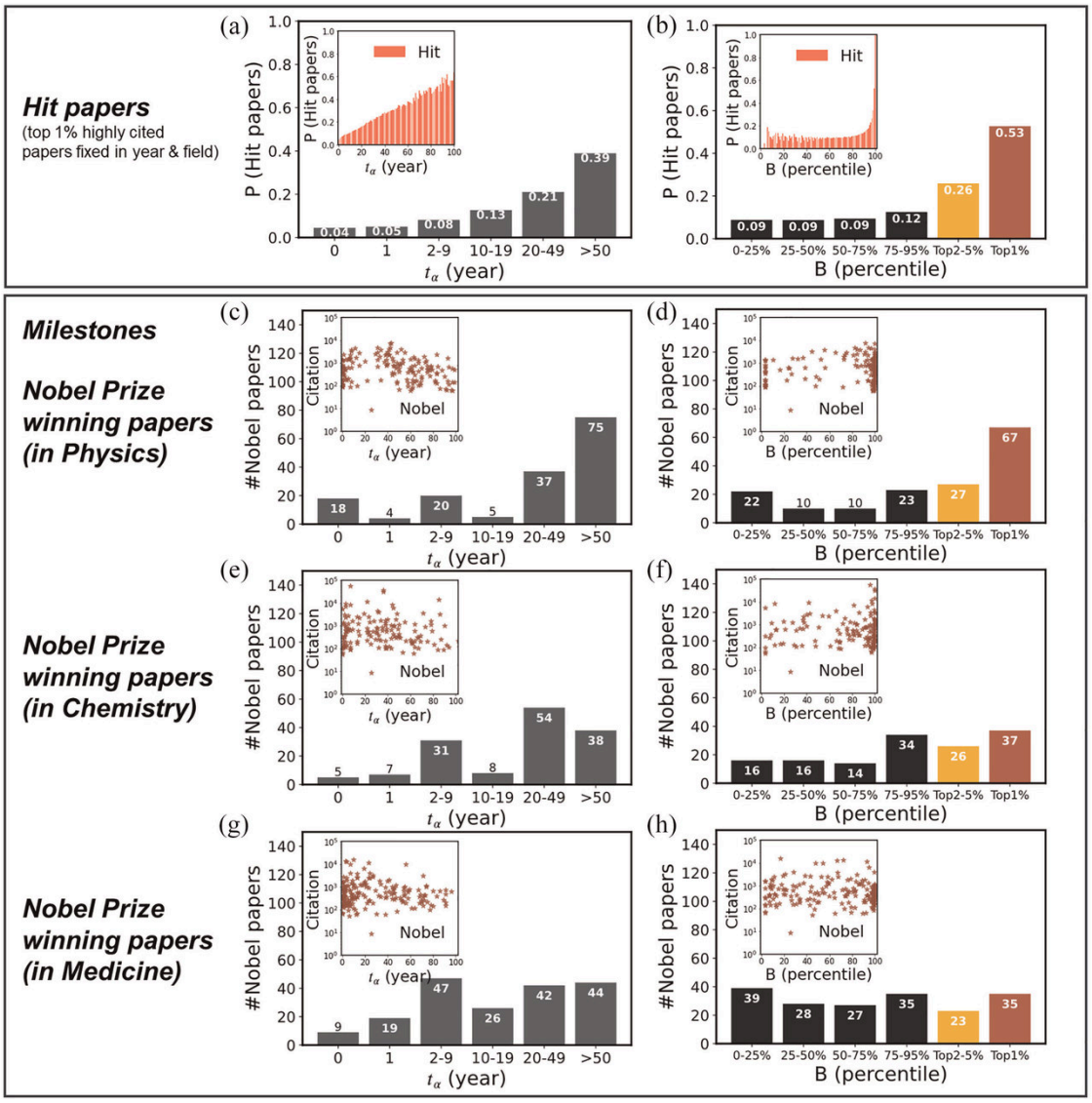


Figure 3. Distributions of hit papers and milestones across distinct levels of delayed recognition in science: (a–b) probability of hit papers (top 1% highly cited papers in their year and field) for different (a) awakening time and (b) beauty coefficients, respectively. (c–h) quantity of Nobel prize-winning papers for different (c, e, g) awakening time and (d, f, h) beauty coefficients, respectively.

4.3. Novelty and disruptive innovation

In addressing RQ3, our analysis delves into the nuanced dimensions of disruption, signifying potential paradigm shifts, and novelty, representing unconventional knowledge amalgamations, within a diverse range of papers exhibiting varied degrees of delayed recognition in science. The results, as presented in Table 3, reveal a significant positive correlation between delayed recognition and both disruption and novelty. Controlling for multiple influential factors, a 1% increase in B is associated with a 2.057% rise in disruption and a 0.4113% increase in novelty. Similarly, a 1% increase in t_α correlates with a 2.864% elevation in disruption and a substantial 0.606% increase in novelty.

It is essential to note that Models 5 and 7 do not exhibit a positive effect, as the control variable, such as the reference count, is not controlled for. Considering that sleeping beauties often possess a smaller number of references, their novelty should be compared with similar papers in this context. These findings suggest a compelling implication: delayed recognition holds the potential to instigate significant disruptions within existing knowledge paradigms. Furthermore, papers characterised by novelty, indicative of unconventional knowledge amalgamations, tend to be associated with delayed recognition in science. This inclination becomes particularly pronounced within the domain of sleeping beauties,

Table 2. The relationship between of scientific hits and milestones, and delayed recognition.

Dependent variable	Hit papers		Nobel (Physics)		Nobel (Chemistry)		Nobel (Medicine)	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent variables								
log (B)	0.1887***		0.3787***		0.4418***		0.1848***	
	(0.0020)		(0.0569)		(0.0598)		(0.0483)	
log(t_α)		0.5776***		0.3616***		0.5861***		0.3679***
		(0.0029)		(0.0794)		(0.0886)		(0.0706)
Control variables								
log (Ref)	0.1724***	0.1891***	0.1586	0.1503	0.0939	0.0885	0.4068***	0.4121***
	(0.0026)	(0.0026)	(0.1067)	(0.1059)	(0.1080)	(0.1077)	(0.0839)	(0.0839)
log (Team size)	−0.0864***	−0.0535***	0.7772***	0.7368***	0.6305***	0.6270***	0.4227*	0.4429**
	(0.0048)	(0.0049)	(0.1376)	(0.1393)	(0.1855)	(0.1856)	(0.1644)	(0.1646)
International	−0.0295***	−0.0380***	0.4430.	0.4432.	−0.1030	−0.1005	0.0615	0.0470
	(0.0067)	(0.0068)	(0.2455)	(0.2424)	(0.2651)	(0.2647)	(0.2237)	(0.2232)
Funding	0.0941***	0.0933***	−10.64	−9.529	−0.6701	−0.7077	0.4865	0.4842
	(0.0105)	(0.0106)	(472.0)	(292.9)	(1.053)	(1.052)	(0.4819)	(0.4818)
log (author age)	0.0833***	0.0550***	0.6605**	0.6845***	0.3601.	0.3632.	0.3600.	0.3353.
	(0.0066)	(0.0067)	(0.2069)	(0.2069)	(0.2136)	(0.2133)	(0.1871)	(0.1878)
log (author pubs)	0.1148***	0.1394***	−0.0779	−0.0830	0.1706	0.1766	0.2222.	0.2372*
	(0.0039)	(0.0040)	(0.1324)	(0.1321)	(0.1226)	(0.1224)	(0.1154)	(0.1158)
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,026,920	2,026,920	84,779	84,779	174,704	174,704	201,646	201,646
Pseudo R2	0.15056	0.17634	0.33406	0.32293	0.21262	0.20936	0.22744	0.2322

Note: All models use Logit regression. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Standard errors are presented in parentheses. Note that the coefficients in Models 3–8 are small because the Nobel-winning papers are only a small proportion of the sample (0.02%).

Table 3. The relationship between innovation and delayed recognition in science.

Dependent variable	Disruption (Pct.)				Novelty (Pct.)			
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent variables								
log (B)	2.577***	2.057***			−0.2205***	0.4113***		
	(0.0141)	(0.0138)			(0.0138)	(0.0133)		
$\log(t_\alpha)$			3.369***	2.864***			0.0080	0.6060***
			(0.0175)	(0.0172)			(0.0171)	(0.0165)
Control variables								
log (ref)		−6.951***		−7.013***		9.136***		9.125***
		(0.0234)		(0.0233)		(0.0246)		(0.0245)
log (team size)		−1.035***		−1.012***		1.957***		1.964***
		(0.0301)		(0.0300)		(0.0286)		(0.0286)
International		0.1264**		0.1107**		0.4894***		0.4862***
		(0.0429)		(0.0428)		(0.0412)		(0.0412)
Funding		0.9668***		0.9443***		1.408***		1.405***
		(0.0582)		(0.0580)		(0.0545)		(0.0545)
log (author age)		0.4093***		0.3652***		−0.0466		−0.0589
		(0.0433)		(0.0432)		(0.0414)		(0.0414)
log (author pubs)		−0.4168***		−0.4001***		0.0915***		0.0976***
		(0.0252)		(0.0252)		(0.0240)		(0.0240)
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Journal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,588,353	1,588,353	1,588,353	1,588,353	1,517,694	1,517,694	1,517,694	1,517,694
R2	0.19365	0.23739	0.19529	0.24007	0.20794	0.27716	0.20781	0.27735

Note: All models use OLS regression. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. Standard errors are presented in parentheses. Disruption and novelty scores are converted into percentile data, following the studies of Wu et al. [19].

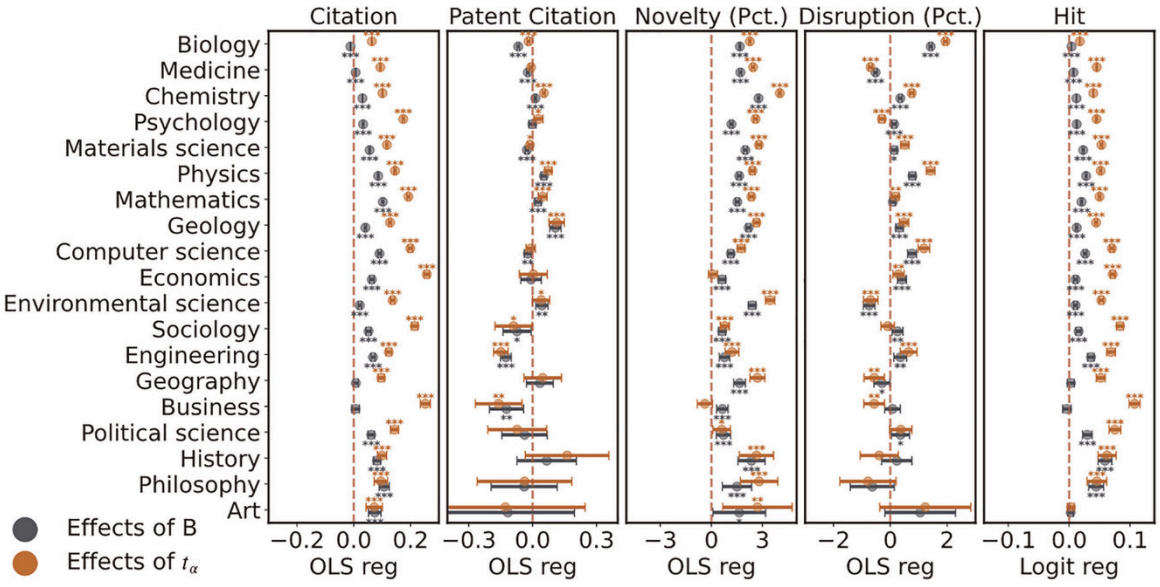


Figure 4. Regression effects of the beauty coefficient (B) and awakening time (t_α) on impact and innovation across diverse fields. All error bars represent 95% confidence intervals based on standard errors (Incorporating control variables, and year and journal fixed effect). *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. The fields are ranked based on the number of papers.

underscoring their propensity to transcend traditional boundaries of knowledge. Ultimately, this predisposition propels their eventual ascent to influential recognition, albeit within the context of a temporally deferred narrative.

4.4. Heterogeneity

Figure 4 offers a comprehensive view of the varied landscape of delayed recognition and sleeping beauties across diverse scientific fields. It presents an array of heterogeneous patterns that shed light on the impact of delayed recognition within each field. The influence of the awakening time (t_α) on scientific impact (citation count and hit rate) remains consistently positive and significant across nearly all 19 fields. However, certain fields such as Geography and Business show insignificant effects of the beauty coefficient (B) on citation count and hit rate, possibly indicating a preference for different dynamics in these domains.

Regarding technological impact (patent citation), significant heterogeneity is observed across fields. Fields such as Art, Philosophy, History and Political Science display insignificant effects of delayed recognition, possibly due to lower citation rates from patents in these areas. Conversely, fields such as Biology and Business exhibit a negative effect of delayed recognition, suggesting a preference for timelier papers rather than sleeping beauties in these domains.

The impact of delayed recognition on novelty consistently demonstrates a positive and significant relationship. This alignment indicates that atypical combinations of knowledge, synonymous with novelty, tend to correlate positively with delayed recognition, supporting the notion of a ‘bias against novelty’ in science [42].

In analysing the relationship between delayed recognition and disruption, most fields display a trend where disruptive papers have a higher likelihood of becoming sleeping beauties. However, exceptions such as Geography and Environmental Science exhibit negative coefficients between disruptive papers and delayed recognition, indicating a different interplay of factors shaping delayed recognition in these specific contexts.

5. Discussion

5.1. Implications

The insights unveiled in this study hold profound implications across various spheres within the scientific landscape, extending to research funding, policymaking and the broader dissemination of knowledge and innovation.

Foremost, our detailed analysis of delayed recognition and the evolution of sleeping beauties offers a fresh perspective on the temporal dynamics of scientific impact. It underscores the limitations of focusing solely on short-term impact

metrics while emphasising the significance of long-term influence. Identifying and tracking the progression of sleeping beauties into canonical milestones highlights the enduring value of research endeavours [16]. Our findings advocate for a balanced approach that transcends immediate metrics in funding decisions and research evaluations. Embracing delayed recognition in assessments can provide a more comprehensive view of research contributions, enriching the understanding of the evolving impact trajectories over time and ensuring a fairer representation of scientific value [64].

In addition, our study reinforces the link between disruptive, novel research and the prevalence of delayed recognition. This emphasises the importance of fostering innovation and supporting research that challenges established paradigms [65,66]. Encouraging the pursuit of groundbreaking concepts, irrespective of their immediate impact, might hold the key to transformative advancements in the future.

Moreover, our identification of fields or research types prone to delayed acknowledgement and subsequent milestone status contributes to understanding the intricate pathways to prestigious recognition in scientific domains. This nuanced understanding aids in delineating the complex processes involved in attaining recognition within diverse scientific realms.

5.2. Limitation and future work

Notwithstanding the comprehensive insights and contributions presented in this article, several limitations warrant acknowledgement, thereby underscoring avenues for potential future research and refinement. First, the examination of delayed recognition and its intricate interplay with various dimensions of scientific impact and innovation inherently necessitates the selection of specific metrics and indicators. The chosen metrics, while well-grounded, might not encapsulate the full gamut of factors contributing to these phenomena. Alternative indicators and metrics could enrich the comprehensiveness of the analysis. Second, the retrospective nature of this study implies that certain contingent variables and external influences could not be fully accounted for in the analysis. Longitudinal studies that encompass real-time observations might offer a more nuanced understanding of the dynamics under scrutiny. Third, the contextual and temporal variations that inevitably characterise the scientific landscape might limit the immediate applicability of these findings across different epochs, disciplines and regions. Accounting for such variations would demand a more nuanced and dynamic approach. Furthermore, the interpretation of correlations, though insightful, cannot necessarily imply causation. Addressing causative relationships and underlying mechanisms would necessitate supplementary methodologies and experimental designs.

In light of the complex and multifaceted nature of the phenomena under investigation, we open some promising avenues for future research. First, a deeper exploration into the selection and refinement of metrics and indicators could enhance the precision and breadth of our understanding of delayed recognition and its interplay with scientific impact and innovation. Comparative analyses involving alternative metrics and the incorporation of qualitative dimensions could enrich the granularity of insights. Second, the adoption of longitudinal research designs, encompassing real-time observations and data collection, holds the potential to uncover the temporal nuances and causal relationships that underlie the emergence of sleeping beauties and their subsequent impact trajectories. Prospective studies could focus on deciphering the cultural, economic and social factors that mediate delayed recognition across diverse fields. Finally, experimental interventions or simulation studies might elucidate the mechanisms that drive the transformation of disruptive and novel research into long-term impactful contributions.

CRediT authorship contribution statement

Alex J Yang: Writing – original draft, Conceptualisation, Methodology, Software, Data visualisation, Validation, Data curation, Resources.
Star X Zhao: Writing – original draft, Conceptualisation, Methodology, Supervision, Funding acquisition, Writing – review & editing.
Sanhong Deng: Conceptualisation, Supervision, Funding acquisition.

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Data availability

The data linkage associated with SciSciNet can be accessed through the following link: https://doi.org/10.6084/m9.figshare.c.6076908.v1. This platform offers unrestricted access to downloadable data files in zip or tsv format, without any limitations or restrictions.
A copy of Microsoft Academic Graph (MAG; v34 as of 24 December 2021), along with the connections to the patents (reliance on Science [55,67]), is openly available at: https://zenodo.org/record/7497435#.Y7y6Qv5BxaY.
The data of Nobel-winning Papers used in this study are open-access at Harvard Dataverse https://dataverse.harvard.edu/dataset.xhtml?persistentId = doi:10.7910/DVN/6NJ5RN.
Other data used in this study can be obtained by making reasonable requests.

Supplemental material

Supplemental material for this article is available online.

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