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ORIGINAL ARTICLE

A Tale of Open Science: Emergence of a New Normal

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Abstract This paper explores the transformative journey of open science in reshaping research credibility and replicability. Using psychology's "replication crisis" as a cautionary tale, we discuss the emergence of open science as a movement aimed at reinforcing transparency and rigor in research practices. Through a discussion of open science principles and practices, we highlight both the successes and challenges that psychology faced in adopting these methods. The paper then draws parallels to

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business research, proposing open science as a necessary evolution to enhance trust and provide actionable insights in fields such as entrepreneurship, sustainability, and digitalization. We invite business researchers to embrace open science's potential, not only to address emerging credibility concerns but also to redefine the impact and reliability of their findings across research fields and industries.

Keywords Open access · Open science · Preregistration · Registered report · Replication

Classification code M30

1 Preamble

This paper embarks on a fairytale story of how psychology slid into a credibility crisis that shook the field to its bones—and it tells how researchers and entire institutions reacted to restore confidence in psychological research. The paper also foreshadows how today's business research is in a similar position as psychology some years ago. By telling this fairytale (see Fig. 1), we aim to provide some guidance for business research on what to learn from the initiatives that several fields in psychology implemented during the last two decades, their merits as well as limitations. We intend to foster debates across business research fields on how open science practices can help to ensure that insights from key research fields like entrepreneurship, sustainability, and digitalization remain valid, credible, actionable, and trustworthy.

We argue that open science fosters cumulative knowledge generation through accessibility and transparency, thus extending its impact beyond individual fields to the long-term sustainability of the business research ecosystem itself. By ensuring that studies across all fields of business research are reproducible, open science fosters a more sustainable—that is, a more resilient and enduring—foundation of our discipline's knowledge base, one that can be trusted and built upon over time by both academics and practitioners. Open science practices thus directly contribute to sustainable knowledge development, echoing earlier calls for greater transparency, reproducibility, and replicability in fields such as marketing (Deer et al. 2025), strategic management (Bettis et al. 2016), and qualitative research (Aguinis and Solarino 2019).

Taken together, open science does more than improve individual studies; it helps shape a broader narrative of progress in business research, laying the foundation for a new chapter in the evolution of our discipline—one that might well begin with "once upon a time" ...

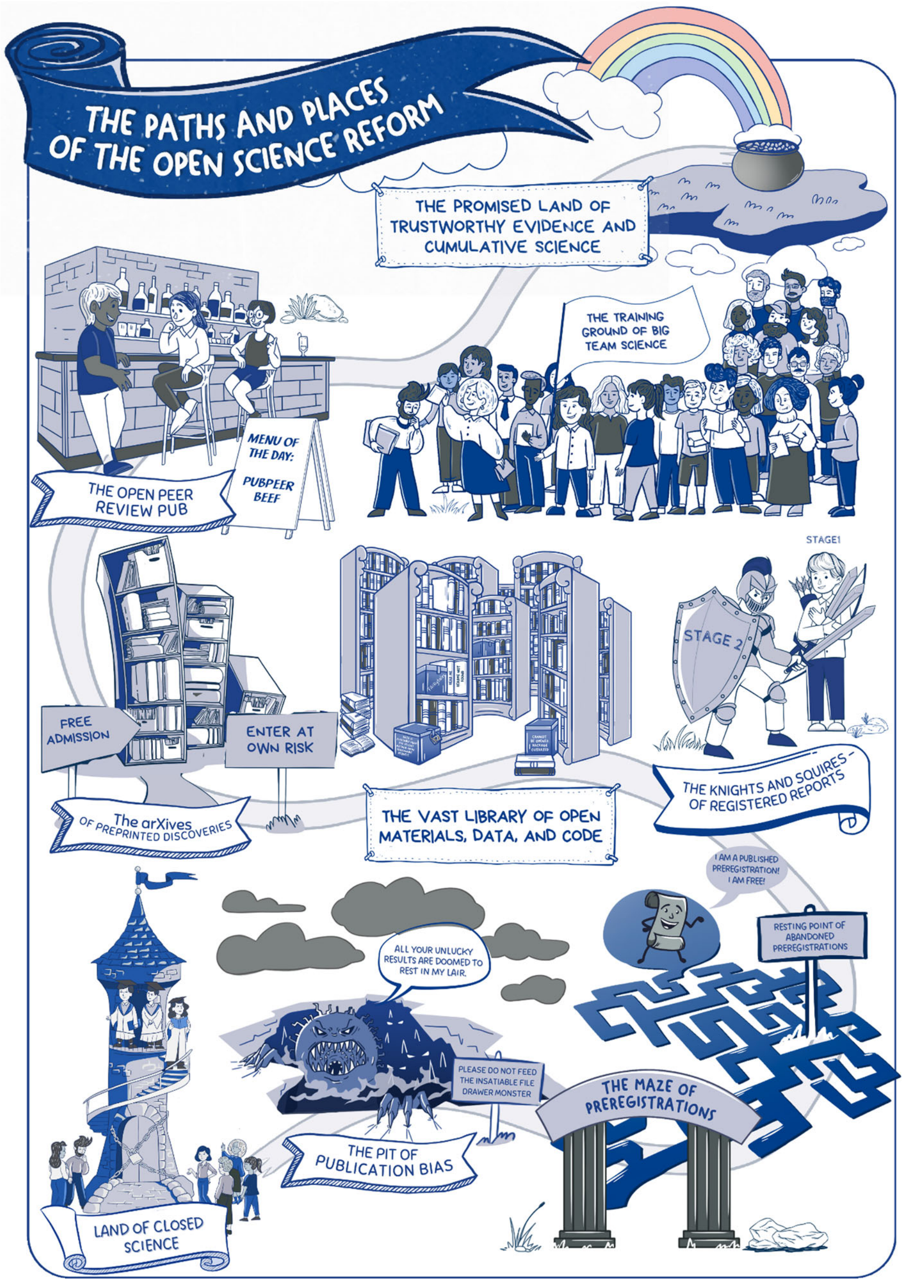

Fig. 1 A fairytale depiction of the path and places of open science within the publication process

2 A Bad Premonition—Dark Clouds on the Horizon

Once upon a time, researchers seemed to live in a world of milk and honey. In this world, science produced an endless stream of interesting and surprising findings. Reported effect sizes were big; papers were rarely retracted and research constantly evolved. People trusted scientific findings. Times were fruitful, they were good.

Over time, however, dark clouds started to loom on the horizon, foreshadowing that something grim was going to come. A nagging feeling started to plague researchers. Suspicion went around that milk and honey might not flow endlessly. Instead, doubt started to lurk around that scientific findings were not as reliable as many researchers thought. The researchers' Shangri-La[1] started to crumble.

One of the first prophecies of a coming storm dates to 2005—the year in which John P. A. Ioannidis published the landmark article "Why most published research findings are false," which, in hindsight, "crystallized the scientific community's awareness of the replication crisis well before the discipline of psychology realized it was in one itself" (Pennington 2023, p. 11). In his article, Ioannidis (2005) pinpointed the adverse effects of underpowered studies and researchers' preoccupation with *p*-values as major sources of excessive false positive rates that—as he argued—had occupied research in medicine and epidemiology. While Ioannidis' (2005) study triggered vast discussions, which are still echoed today across disciplines (e.g., Bultez and Herrmann 2025), it was Bem (2011) that darkened the clouds and nudged psychological sciences into a state of doubt (Engber 2017). In a series of nine experiments, Bem (2011) provided empirical support for precognition, showing that causal stimuli that occurred *after* recording participants' responses impacted their behavior. Soon after its publication, several researchers voiced concerns about Bem's (2011) research design and statistical analysis (Wagenmakers et al. 2011), with efforts to replicate the effect being unsuccessful (Galak et al. 2012; Ritchie et al. 2012).

Over the following years, more and more mists engulfed psychological findings. Diving into these mists revealed that studies with nonsignificant results, which had been buried in a file drawer, had important implications for researchers' conclusions about the size and existence of fundamental effects. Specifically, taking publication biases—triggered by the research system's tendency to report and publish only significant results—into account, yielded notably lower replication rates of seminal effects such as priming (Doyen et al. 2012) and ego depletion (Hagger et al. 2010; Vohs et al. 2021). One of the most prominent articles originated from the Open Science Collaboration's reproducibility project psychology (Open Science Collaboration 2012, 2015). The researchers attempted to replicate 100 psychological studies from the fields of cognitive and social psychology and found that only 39 of these studies replicated the original results. Multiple large-scale replication projects (e.g., Ebersole et al. 2016; Ijzerman et al. 2020; Klein et al. 2022, 2014, 2018) followed as well as structured approaches to collect data on replicability and reproducibility (Brodeur et al. 2023; Röseler et al. 2024) along with meta-scientific studies about

[1] Shangri-La is a fictional place from the 1933 novel 'Lost Horizon,' symbolizing a peaceful paradise or ideal retreat from the world.

researchers' degrees of freedom and their impact on research findings' validity and replicability (e.g., John et al. 2012; Pashler and Wagenmakers 2012; Simmons et al. 2011). Although some of these projects have been criticized themselves (e.g., Altmejd et al. 2019; Baumeister et al. 2023; Gilbert et al. 2016), the resulting debates initiated a shift in psychological science toward a new dawn.

3 The Dark Clouds are Spreading

Dark clouds not only gathered over psychology, but they started to loom over other disciplines as well. Over the last years, evidence surmounted that fundamental effects established in various business research fields are not as replicable as we would desire them to be (Spellman et al. 2017). Take, for example, marketing and consumer research. Recent efforts to replicate seminal effects in the field were either not successful or yielded notably smaller effect sizes. Examples include the relationship between decision conflict and choice deferral (Evangelidis et al. 2022), the effects of product scarcity (O'Donnell et al. 2021) as well as estimates for TV advertising effectiveness (Shapiro et al. 2021). At the same time, meta-analyses cast doubt on the impact of prominent phenomena such as nudging (Maier et al. 2022). Related findings outline a publication bias in consumer research that favors significant findings and may obscure non-significant or inconclusive results (Adler et al. 2023a; Brodeur et al. 2022). Indeed, average replicability rates of major consumer research journals are rated well below those from other fields of behavioral and brain sciences (Dougherty and Horne 2022). To make things worse, marketing articles often do not provide sufficient information to enable effective replications (Adler et al. 2023b; Lehmann and Bengart 2016), and marketing journals only publish a negligible number of replication studies (Tipu and Ryan 2022).

Cynical observers may hope that the dark clouds hang over marketing and consumer research only—but this is not the case. Similar concerns have been raised in fields such as finance (Hou et al. 2020), international business (Aguinis et al. 2020), and operations management (Davis et al. 2023), sometimes triggering debates about the studies' conceptual underpinnings and methods used (e.g., Aguinis et al. 2020).

This cascade of grim omens has started sowing doubts about the accuracy of research results far beyond the psychological sciences or consumer research. It is indeed a symptom of a deeper threat to science: The growing superstition that many (business) research findings are not as reliable as we want or need them to be to give useful practical and policy advice. While one may debate whether our discipline is truly encountering a replication *crisis*, there is no doubt that concerns about replicability start to shake business research's credibility.

4 The Emergence of a Hero? Open Science to the Rescue!

To avoid rushing into a situation of similar magnitude as the psychological sciences, business researchers are well-advised to scrutinize how the fields responded to reinstate credibility. In a nutshell, most psychological fields—including their journals, universities, and funding institutions—implemented fundamental procedural changes that sought to increase research transparency and credibility (Korbmacher et al. 2023; Pennington 2023). These changes came in the form of the Open Science Movement. Open science is "*an umbrella term reflecting the idea that scientific knowledge of all kinds, where appropriate, should be openly accessible, transparent, rigorous, reproducible, replicable, accumulative, and inclusive, all which are considered fundamental features of the scientific endeavor. Open science consists of principles and behaviors that promote transparent, credible, reproducible, and accessible science.*" (Parsons et al. 2022, p. 314). Guided by open science principles, researchers started to rebuild the ways in which they conduct and report as well as what criteria they use to evaluate research (e.g., Vicente-Saez and Martinez-Fuentes 2018; Wagenmakers et al. 2021) with implications far broader than simple changes to the protcol. Some researchers consider open science a fundamental part of a broader movement toward openness in all aspects of society (Pennington 2023), since "openness [seems to] provide the best possible conditions for producing knowledge and, therefore, making better decisions" (Tkacz 2012, p. 389).

A legion of approaches, ideas, and grassroots movements pushed to make research more transparent and robust (e.g., Deer et al. 2025). The most prominent practices can be aligned with three stages in the research process and constitute preregistrations (Nosek et al. 2018), registered reports (Chambers and Tzavella 2022; Nosek and Lakens 2014), collecting data from big team science projects (Forscher et al. 2022), making materials, data, and code openly accessible (Wilkinson et al. 2016), fostering open access and preprints (Moshontz et al. 2021), as well as engaging in open evaluation and peer review (Ross-Hellauer and Görögh 2019; https://pubpeer.com/; https://peercommunityin.org/). Table 1 documents the various open science practices and provides an overview of their advantages as well as drawbacks.

To structure our journey along the open sciences practices, we clustered them along the traditional research process. The first stage refers to designing the study and preparing the manuscript. Open science practices relevant in this stage include preregistrations, registered reports, and, more broadly, big team science projects. The second stage includes the submission of the manuscript and the peer review process and pertains to making materials, data, and code openly available in open evaluation and open peer review. The third stage refers to the publication of the manuscript which includes open access and preprints.

In discussing various open science practices, we recognize that they cannot always be clearly categorized, as they may apply to multiple stages simultaneously. For example, while open data is important in the peer review process to safeguard reproducibility prior to manuscript acceptance, it is fundamental for follow-up research on the same topic (e.g., in the context of meta-analyses). We will briefly discuss these interdependencies and synergies after describing the open science practices across the three stages of the research process.

4.1 Stage 1—Research Design & Manuscript Preparation

The first stage refers to all activities prior to manuscript submission, such as designing and conducting a study, analyzing the results, and preparing the manuscript.

Table 1 Overview of open science practices.

Stage	Type	Description	Advantages	Drawbacks	Suggested reading
Stage 1—Research design and manuscript preparation	Preregistration	Registering a study protocol (e.g., research questions, hypotheses, design, variables, data analysis plan) in a dedicated document that is uploaded to a public platform (e.g., the Open Science Framework, OSF, https://osf.io/registries; or AsPredicted, https://aspredicted.org/) before data collection or analysis	Makes researchers' degrees of freedom transparent Mitigates questionable research practices Improves reproducibility	Difficult to implement in cases where data handling and analysis can hardly be anticipated Emphasis on hypothetico-deductive theory testing at the expense of inductive research Higher workload for researchers and reviewers May favor conservative designs Documentation may be too vague to be useful Potential excessive rates of abandoned preregistrations	Hardwicke and Wagenmakers (2023); Mellor and Nosek (2018); Nosek et al. (2019, 2018)
	Registered report	A study proposal is reviewed before the research is undertaken. Proposals that meet high scientific standards are then provisionally accepted before the outcomes are known, and the full paper will be published independently of the results	*Same as for preregistrations plus:* Overcomes issues of underpowered research or weak experimental designs by requiring an early peer review process Takes focus away from significant results as a central criterion for acceptance at a journal (publication bias) Mitigates the file drawer problem	Mostly the same as for preregistrations	Chambers and Tzavella (2022); Hardwicke and Ioannidis (2018); Henderson and Chambers (2022); Nosek and Lakens (2014)
	Big team science projects	Open, large-scale collaboration between researchers to address fundamental research questions and pool resources across different labs and institutions	Increase in diversity and representation of participants and researchers Enable testing differences between labs to examine an effect's generalizability or robustness (e.g., across multiple cultures) Allow for more rigorous and reliable large-scale studies Mitigates questionable research practices A high degree of standardization facilitates reproducibility Typically comes with open material, data, and code	Coordination requires substantial effort Large effort may not be reasonable for all research questions	Brodeur et al. (2023); Brodeur et al. (2022); Forscher et al. (2022); Kvarven et al. (2020)

Table 1 (Continued)

Stage	Type	Description	Advantages	Drawbacks	Suggested reading
Stage 2—Submission & peer review	Open materials, data, and code	Project files, including protocols, survey questions, instructions, stimuli, data, and computer code are made available to the public without restrictions, allowing anyone to access, use, modify, and share them	Improves reproducibility	Incomplete documentation can lead to misinterpretation of data and results	Colavizza et al. (2020); Rouder (2016); Wilkinson et al. (2016)
			Enhances cumulative knowledge generation	Lack of acknowledgment for sharing material, data, or code whose generation/collection may have required much effort	
				Potential privacy and anonymity, intellectual property rights, or copyright issues	
				Fear of criticism or uncovering mistakes	
	Open evaluation and open peer review	A peer review model in which aspects of the peer review process are made publicly available, either before or after publication. Open peer review includes unveiling reviewer and author identities, publishing (anonymous) review reports along the accepted manuscripts, and allowing to publicly contribute to the peer review process	Reduces reviewer conflicts of interest	Prolonged review time	Dobusch and Heimstädt (2019); Ross-Hellauer (2017); Walsh et al. (2000); Wolfram et al. (2020)
			Mitigates plagiarism and data fabrication	Risk of bias and favoritism	
			Encourages collaboration and dialogue	Herd mentality where reviewers may feel pressured to align their views with those of others	
			Educational value	May induce self-promotion	
			Improves public understanding of the scientific process		
			Discloses predatory journals		
			Recognizes and appreciates reviewer work		
Stage 3—Manuscript publication	Open access and preprints	Making papers, chapters, books, or other scholarly works publicly available with minimal barriers to access. Scientific documents may also be made available legally outside of a traditional publisher in the form of preprints, published on dedicated servers such as arXiv, PsyArXiv, or SSRN	Accelerates scientific discussion and dissemination	Substantial open access fees disadvantage researchers from resource-poor environments	Fraser et al. (2020); Moshontz et al. (2021); Sarabipour et al. (2019)
			Greater public exposure	Quality concerns	
			Increases citations	Preprints may not have gone through peer review	
				Preprints may hinder follow-up publication in a journal	

Researchers may draw on preregistrations or submit their research framework in the form of a registered report. Research projects can also take the form of big team science initiatives, incorporating diverse research designs and approaches to documenting results.

Preregistration involves documenting a study's research questions, hypotheses, methodology, and analysis plan (ideally) *before* the data collection and the actual data analysis. This information is publicly registered on platforms like the Open Science Framework (OSF; https://osf.io/registries) or AsPredicted, (https://aspredicted.org/). A preregistration includes a time stamp to confirm that the study was preregistered before the analysis commenced (van't Veer and Giner-Sorolla 2016). The aim of preregistering a study is to enhance the transparency and credibility of scientific research. By disclosing all analyses upfront (Simmons et al. 2021b), researchers can mitigate selective reporting and *p*-hacking practices (Sarstedt and Adler 2023).

An increasing number of journals, particularly in the field of psychology, have embraced the concept underlying preregistrations by publishing *registered reports* (Hardwicke and Ioannidis 2018). This publication format entails peer-reviewing and, given favorable reviews, accepting a study's research questions, methods, and proposed analyses prior to data collection (Chambers and Tzavella 2022). If studies are conducted and analyzed as proposed in the Stage 1 manuscript, the final Stage 2 manuscript will then be published regardless of the analysis results. This approach enhances research's credibility by ensuring that studies are evaluated based on their theoretical and methodological rigor rather than the results obtained. Substantiating the growing importance of preregistrations, more than 300 journals offer the registered report format currently (for a comprehensive list, see: https://www.cos.io/initiatives/registered-reports).

Finally, *big team science projects* (e.g., in the form of many-lab projects or many-analyst studies) are large-scale collaborations between researchers to address fundamental research questions and pool resources across different labs and institutions (Forscher et al. 2022). For example, a preregistered project with 36 laboratories and more than 3500 participants didn't find support for an ego-depletion effect after exercising self-control (Vohs et al. 2021). The Construal Level International Multilab Replication Project (CLIMR) project unites 78 labs from 27 countries for collectively gathering data in 15 different languages to assess the robustness and reproducibility of key construal level theory findings across diverse contexts and samples (Calderon et al. 2023). Big team science projects can also take the form of many-analysts' studies, where multiple researchers analyze the same data set to test a single model but apply different analytical methods (Sarstedt et al. 2024a). For example, Breznau et al. (2022) let 161 researchers from 73 teams analyze the same data to independently test whether more immigration reduces public support for social policies. The teams' results varied considerably, ranging from large negative to large positive effects of immigration on social policy support. While big team science projects can be regarded as the gold standard for assessing the robustness of certain phenomena (Forscher et al. 2022), initiating and managing them is very challenging in terms of rewarding participating researchers, ensuring diversity, and funding (Coles et al. 2022).

4.2 Stage 2—Submission & Peer Review

In the second stage, researchers submit their manuscript, potentially including a preregistration or in the form of a registered report, to a peer-reviewed journal. At this stage, researchers choose to make their materials (e.g., stimulus material), data, and or (analysis) code available, also for peer review. Depending on the journal, reviewers may need to decide whether they want to engage in an open peer review process.

Making materials, data, and code openly available is a fundamental building block of open science to increase transparency and facilitate reproducibility. In doing so, researchers should adhere to the FAIR principles according to which the files should be (f)indable, (a)ccessible, (i)nteroperable, and (r)eusable (Wilkinson et al. 2016). While data sharing improves reproducibility and enhances cumulative knowledge generation, data protection laws and copyright requirements may act as barriers to its implementation (Guzzo et al. 2022). Leaving legal concerns aside, researchers are frequently reluctant to openly share material, data, and code whose collection and generation require much effort as they do not receive sufficient credit for it. This is also evidenced in the results of a large-scale cross-disciplinary survey of researchers regarding open science practices by the *Leibniz Information Centre for Economics* (Siegfried et al. 2024). Their results show that approximately 40% of all researchers who work empirically, voiced concerns about lacking recognition of data sharing. However, such gatekeeping—while being rewarded by standard academic incentive structures—opposes the general quest of science to generate knowledge for society.

To further the implementation of preregistration, open materials, and open data, an increasing number of psychology journals such as *Psychological Science* require authors to implement open science statements in which they explain if their study was preregistered and whether materials, data, and analysis scripts are made openly accessible (Hardwicke and Vazire 2024). Based on these statements, some journals award open science badges for preregistering the study and making materials and data publicly available. Currently, more than 100 journals implement such badges (for a list of all journals, see: https://www.cos.io/initiatives/badges). Although one may argue that awarding badges is immature, research demonstrates that implementing open science badges is associated with increasing social media attention (Zong et al. 2023) and a higher rate of data sharing, mainly because seeing colleagues practice open science signals that new community norms have arrived (Kidwell et al. 2016).

In *open peer review*, elements of the review process are made publicly available. Open peer review may include various disclosure levels such as unveiling reviewer and author identities, publishing review reports, and allowing to publicly contribute to the peer review process. A journal that has embraced open peer review from the start is *Meta Psychology* where the entire editorial process is openly accessible for anyone to assess, regardless of whether a manuscript is ultimately published or rejected (Carlsson et al. 2017). Manuscripts are not only subjected to a traditional peer review but are also posted online (https://open.lnu.se/index.php/metapsychology/about), exposing each paper to many potential peer reviewers. Similarly, *Psychological Science* has recently transitioned to "transparent peer review," which entails publishing anonymized reviewer reports, editors' decision letters, and authors' responses of accepted manuscripts to "help surface any problematic patterns" in peer review processes (Vazire 2024, p. 706).

4.3 Stage 3—Manuscript Publication

In the third stage, questions about the publication of the manuscript arise. Authors and reviewers need to decide if they want to publish their work open access and as preprints. *Preprints and open access options* have become somewhat of a norm in business research. In this stage, researchers decide to make their work publicly available with minimal barriers. This does not necessarily include publishing within the realm of a traditional publisher but can include preprint servers such as arXiv, PsyArXiv, or SSRN or other outlets (e.g., Fraser et al. 2020; Moshontz et al. 2021; Sarabipour et al. 2019).

4.4 Synergies Between Open Science Practices

The open science practices discussed above are neither mutually exclusive nor strictly bound to these stages in all cases. Preregistration and registered reports establish a foundation for research transparency by requiring researchers to document their hypotheses, methods, and analysis plans in the early stage of the research process. These efforts naturally align with open science practices in stage 2 such as open materials, data, and code. These practices seek to enhance reproducibility and transparency, not only in the peer review process but also after manuscript publication in stage 3. Specifically, sharing data and code allows other researchers to critically assess the study or use its data as input for follow-up analyses, potentially using improved estimators. For example, Maier et al. (2022) used a robust Bayesian meta-analysis to account for publication bias in a previous meta-analysis on nudging (Mertens et al. 2022), concluding that "after correcting for this bias, no evidence remains that nudges are effective tools for behavior change." Providing reusable materials thereby facilitates building on previous research projects, making business research more efficient. Large-scale, multi-institutional collaborations further reinforce these practices by emphasizing transparency, openness, and teamwork. By relying on shared data, preregistered methodologies, and collaborative workflows, big team science projects encourage cooperative research.

To summarize, implementing open science practices across all stages of the research process fosters a culture of openness, collaboration, and credibility, potentially enhancing the reliability and impact of scientific work. This transformation helps move academic research beyond the limitations of selective reporting and unpublished findings, setting the stage for a more trustworthy and cumulative scientific enterprise, as illustrated in the story map at the beginning of this article.

5 The Ongoing Quest for Transparency and Replicability

It may be tempting to focus solely on the bright side of open science, glorifying it as a hero that is "saving science." However, while heroes in fairytales are often flawless and virtuous, our hero is not as perfect as its shining armor may suggest at first glance. Indeed, despite noble efforts, internal struggles, challenges as well as myths surround open science. Some observers might see these struggles as merely superficial stains on an adamantine armor while others might see the armor already crumbling. There is always some truth to the word on the streets—indeed open science initiatives and practices also come with problems and pushbacks that relate to their effectiveness in tackling credibility problems, practicability in their implementation, and accessibility to researchers from resource-poor environments (e.g., Bahlai et al. 2019; Baumeister et al. 2023; Deer et al. 2025; Guzzo et al. 2022; Hostler 2023; Pham and Oh 2021b). Let the story unfold ...

5.1 Preregistrations & Registered Reports

Given the substantial overlap of preregistrations and registered reports (see Table 1), we will discuss the drawbacks of both open science practices jointly.

Limited Foresight Both preregistrations and registered reports require a high level of foresight, as many decisions must be made prior to data collection. Researchers must anticipate how to handle potential complications during data collection and analysis, which can be challenging. For example, researchers may encounter difficulties recruiting the number of preregistered participants or may discover new methodologies that were not considered during the preregistration process. In such cases, researchers must transparently disclose how and why they deviate from their initial plans (Chambers and Tzavella 2022; Nosek et al. 2018). This allows readers, reviewers, and editors to assess these deviations and estimate potential biases. Moreover, deviations might even be desirable if researchers identify mistakes in their preregistrations, but these changes must also be disclosed transparently (Hardwicke and Wagenmakers 2023; Lakens 2024; Oberauer and Lewandowsky 2019).

Restrictiveness Critics argue that preregistrations and registered reports can be overly restrictive. Because everything must be predetermined, researchers may overlook interesting patterns that emerge during analysis, hindering serendipitous findings (Chambers and Tzavella 2022; Leavitt 2013). This issue is exacerbated by the necessity to label unanticipated findings as exploratory research, which may undermine confidence in these results. This label draws attention to preregistered analyses, and it can overshadow exploratory results. However, such labels do permit researchers to conduct exploratory analyses and publish their findings (van't Veer and Giner-Sorolla 2016). Additionally, these practices can help protect serendipitous findings from publication bias, as preregistrations establish a baseline for analysis prior to data collection (Chambers and Tzavella 2022).

Higher Workload for Researchers and Reviewers Preregistrations and registered reports are often seen as effortful, time-consuming, and burdensome. For example, researchers frequently conduct multiple experiments in a short timeframe, which can make open science practices feel like a hindrance to efficiency. Preregistrations require thinking deeply about the study design and the analysis plan at a level of detail that may otherwise not have occurred. At the same time, researchers might conduct several exploratory studies before preregistering a study plan. Communicating this procedure transparently as well as creating a preregistration or a registered report for subsequent replications can maintain a high level of efficiency while still allowing for exploratory data collection (Nosek et al. 2018). Preregistrations increase the workload for reviewers, especially in multi-study and multi-method papers across various review rounds. For instance, an average paper published in the *Journal of Consumer Research* between 2021 and 2022 included eight studies (Breuer et al. 2023). It seems unlikely that reviewers will have the capacity to compare each preregistration with the manuscript draft over multiple rounds of reviews. While the high workload may slow the publication process—particularly impacting early-career researchers—preregistration can mitigate publication bias and enhance the chances of publication (Chambers and Tzavella 2022).

Limited Applicability The applicability of preregistration and registered reports may be limited as it depends on their suitability for certain research fields and related research methodologies. Critics argue that preregistrations and registered reports are only applicable in research projects with well-defined hypotheses and methodologies. This makes them more appropriate for hypothetico-deductive testing rather than inductive or exploratory research (Chambers and Tzavella 2022; van't Veer and Giner-Sorolla 2016). However, also vague predictions as well as exploratory analyses can be preregistered. Moreover, exploratory research can yield insights that inform subsequent predictions (Nosek et al. 2018). For those using pre-existing or longitudinal data, preregistration is still possible if researchers refrain from examining the data beforehand. Furthermore, new variables and analyses can be preregistered as they are added in longitudinal studies (Nosek et al. 2018).

Favoring Conservative Designs There is an argument that registered reports and preregistrations may favor conservative, "safe" research questions and designs. Knowing that their methods and analyses will be scrutinized, researchers might opt for "safer" rather than innovative, high-risk designs as it will be clear which findings were (un-)expected (Vazire 2018).

Vagueness It is essential to recognize that the level of detail and clarity in these preregistrations can vary significantly (Hardwicke and Wagenmakers 2023; van den Akker et al. 2024). Researchers may, intentionally or unintentionally, choose to remain vague in their descriptions or may leave certain design elements out (van't Veer and Giner-Sorolla 2016). While this flexibility is not inherently problematic, it contradicts the purpose of being as specific as possible when preregistering their studies or issuing a registered report. Indeed, research indicates that this specificity is often lacking in these two practices (Claesen et al. 2021; Ofosu and Posner 2020).

Changing social norms and establishing standard operating procedures, for example, in the form of templates can help address this challenge.

Abandoned Preregistrations Abandoned preregistrations refer to instances in which researchers initially preregister their study but do not publish its findings. This can occur for various reasons, including logistical reasons such as changes in a research portfolio or starting a new job, null results that discourage researchers from publication, requests during the review process, or unforeseen methodological challenges and mistakes (Ensinck and Lakens 2025). Abandoned preregistrations can create gaps in the research record, potentially leading to publication bias if only certain studies are shared. Similar to not disclosing deviations from preregistrations, abandoning preregistrations can lead to the impression that everything went according to plan (Claesen et al. 2021).

5.2 Big Team Science Projects

Organizing a large team of scientists from diverse backgrounds, institutions, and time zones poses significant logistical challenges. Effective coordination, management of timelines, and communication within a large team require substantial administrative efforts, which can detract from actual research activities. Poor coordination can result in confusion, missed deadlines, and duplicated efforts (Forscher et al. 2022). Big team science projects therefore demand significant administrative support, such as project managers and technical staff. These additional roles increase overhead costs, which can strain project budgets and divert resources from core research activities. Securing adequate funding is essential to facilitate such research (Forscher et al. 2022).

5.3 Open Materials, Data, and Code

Incomplete Documentation Releasing raw datasets without context or structure does not facilitate reproducibility or the development of a cumulative knowledge base. Such practices can lead to misinterpretation of data and results. Instead, researchers should provide accompanying documentation, such as codebooks, ReadMe files, and metadata, to clarify how the data is structured, how it was analyzed, and what generalizations can be made (Deer et al. 2025; Hardwicke and Vazire 2024).

Lacking Recognition Publishing in academic journals remains the primary currency for researchers. As a consequence, researchers may view the value of sharing their data, code, and materials as limited (Soeharjono and Roche 2021). Considering that preparing and documenting data for sharing is time-consuming and increases workload, the perceived benefits may not outweigh the effort (Perrier et al. 2020). Addressing this issue, the open science framework is currently developing the *Lifecycle Journal*, which aims to recognize researchers' contributions throughout the research process, from conceptualization over data sharing to reporting (https://www.cos.io/lifecyclejournal).

Copyright and Privacy Issues Concerns over intellectual property and ownership may deter researchers from sharing their data, fearing improper use without attribution (Asswad and Gómez 2021). Similarly, researchers frequently note that sharing data may induce privacy issues. Even with anonymization, risks of re-identification persist, particularly in small datasets. Thus, sharing data must be approached carefully to avoid harming vulnerable groups and infringing on ethical norms. Professional anonymization is essential.

Insecurity and Drawing Criticism Researchers, particularly early-career researchers, may hesitate to release their data, code, and materials due to insecurity about data preparation and analysis (Gomes et al. 2022). Fears of criticism or uncovering mistakes can impact a researcher's decision to publish the data, code, and materials. However, mistakes are inevitable in research; shifting the narrative around errors—emphasizing that they are acceptable when unintentional—can encourage researchers to share their work. Additionally, sharing with trusted colleagues for review and support can provide guidance on effective publication (Gomes et al. 2022).

5.4 Open Evaluation and Open Peer Review

Prolonged Review Time Reviewers might invest more effort into crafting their reports if they know that these will be available openly. Open peer review therefore may prolong the time it takes a researcher to write a review compared to anonymous reviews (Bravo et al. 2019). Whereas predatory journals are quick to accept a manuscript based on low-quality or no review process, open peer reviews can help to disclose predatory journals as the review process is done transparently (Dobusch and Heimstädt 2019).

Repercussions Some reviewers may hesitate to participate in open peer review due to concerns about backlash or strained professional relationships, particularly when critiquing the work of well-known or senior researchers. This fear can reduce the willingness of qualified experts to review or may lead to overly cautious feedback (Ross-Hellauer 2017; Tennant et al. 2016). However, initial evidence indicates that many authors do not share this fear since nearly half (46%) of the authors who submitted their work to *Nature* chose to publish their peer reviews. It should be noted though that this percentage varies significantly across research disciplines (Nature 2022). Knowing their reviews will be public, reviewers may put more effort into their work, but may also avoid providing critical feedback to prevent controversy, thereby undermining the review process' rigor (Ross-Hellauer et al. 2017; Walsh et al. 2000).

Self-Promotion Public recognition of reviewers creates opportunities for self-promotion. In an open review setting, reviewers may feel pressured to showcase their expertise, potentially shifting the focus from improving the manuscript to enhancing their visibility. This dynamic could detract from the objective of providing constructive feedback (Tennant et al. 2016). However, as there are multiple entities involved in the review process, this risk may be smaller than feared. There should be a self-corrective mechanism within the review process as the editor and other reviews will know who provided the review.

5.5 Open Access

High Publication Costs One of the most apparent drawbacks of open access is the high publication costs associated with it. Many open access or hybrid journals require authors to pay article processing charges (APCs), which can be prohibitively high (Dallmeier-Tiessen et al. 2011). Institutions need to provide the funds to allow such publications. Researchers with better funding are often more able to afford APCs, potentially creating disparities in publication output. This inequity can exist between well-funded and underfunded researchers and institutions (Shah 2017). It is crucial to consider how processing fees are applied and to provide support for researchers who cannot afford these costs. This situation is particularly challenging for researchers from resource-poor countries or for early-career scholars without institutional support. Institutions must guide and provide funding for APCs. Many publishers however allow authors to share the latest version of the manuscript openly (e.g., on preprint servers).

Quality Concerns and Predatory Journals The open access model has been accompanied by a rise of predatory journals that exploit the pay-to-publish system, often lacking rigorous peer review and publishing low-quality research. Predatory journals are quick to accept manuscripts and conduct either no peer review or only superficial peer reviews to allow for an immediate publication (Xia 2015). This trend undermines the credibility of open access publishing (Shah 2017) and may be fortified by journals that charge small fees and promise fast publication (Greussing et al. 2020). The research community must remain vigilant regarding these predatory practices.

5.6 Preprints

Lack of Quality Preprints are often shared without formal peer review, increasing the risk of disseminating unverified or flawed research. This may result in papers being cited without having undergone peer review, thereby lacking quality (e.g., Berg et al. 2016). Researchers must be cautious when interpreting preprints, given their unverified status.

Potential for Misinterpretation Because preprints are freely accessible, their findings may be misinterpreted by journalists, other researchers, and the public as established facts. This misrepresentation can lead to sensationalized or inaccurate media coverage (e.g., Raynaud et al. 2021). Researchers can address this issue by providing additional context, such as disclaimers or cautious executive summaries.

Potential Restrictions on Journal Publications Not all journals may accept submissions of papers that were previously published as preprints. Given that publication in prestigious journals is the primary currency in academia, this can pose a challenge for researchers when deciding how to publish their work (Berg et al. 2016). A cultural debate is needed within the research community on whether to accept preprints as one form of publication.

6 The Bigger Picture

With this paper, we aim to provide a neutral overview of the current state-of-the-art in open science, presenting both its advantages and challenges in a manner that is accessible and engaging for business researchers. Our goal is to offer a balanced summary of the open science movement, its practices, and their implications for business research, without advocating for any particular philosophical stance. While we present open science as a set of practices designed to enhance transparency, replicability, and methodological rigor, we also recognize that these practices are grounded in specific epistemological assumptions.

Our descriptions align with critical realism, which posits that while an objective reality exists, scientific inquiry can only approximate it and that knowledge evolves over time. Critical realism emphasizes that our understanding of reality is always mediated by our perceptions and conceptual frameworks (Rousseau 2020). As such, it values the replication of findings insofar as it helps refine theories and uncover deeper causal mechanisms (Mir and Watson 2001). While critical realism is a form of scientific realism, it differs from more naïve versions by emphasizing that the truth about the world is often indirect and can only be approximated through evolving scientific practices. In contrast, traditional scientific realism tends to assume that theories progressively offer increasingly accurate representations of an objective reality. Scientific realists maintain that scientific theories not only reflect the world but also approximate its objective nature, even as these representations may evolve over time (Boyd 1983).

We acknowledge that alternative paradigms, such as constructivism, offer contrasting views. Constructivists argue that knowledge is socially constructed and context-dependent, emerging through discourse, practice, and interpretation. They challenge the assumption that knowledge should replicate across contexts, as this implies a stable, mind-independent reality—an idea they critique. For constructivists, knowledge evolves dynamically and is shaped by social and historical contexts rather than building in a linear, cumulative fashion. The very notion of cumulative knowledge is considered problematic, as knowledge is seen as fluid, situated, and contingent (Mir and Watson 2001). While we adopt critical realism as the framework for our view of the replication crisis and for understanding the open science movement, we do not endorse any specific framework as the "right" one.

This divergence opens several avenues for future research in the field of open science within business research. One promising direction is to explore how varying epistemological stances shape the interpretation and practical application of open science practices. Another fruitful approach would be to conduct comparative studies that assess the outcomes of these practices across different philosophical frameworks, thereby evaluating their impact on research transparency and reproducibility. A potential pathway involves developing integrative models that bridge the divide between different perspectives, aiming to foster a more comprehensive understanding of how philosophical plurality can enhance the open science movement in business research. On the one hand, some scholars argue that the social sciences, which may include business research, should aim at detecting causal relationships that allow the establishment of basic principles that can be unraveled in different contexts (e.g., Mills 1969). On the other hand, others argue that findings and theories in the social sciences are limited to a particular time and place (e.g., Gergen 1973). With cultural changes, basic principles will be revised. At least partial support for this notion comes from research showing that the success rate of replicating social psychological findings strongly depends on contextual factors, including time, culture, location, and population (van Bavel et al. 2016). Thus, a promising avenue for future research could be to investigate how landmark findings in business research last over time as well as across cultures and samples (for a similar approach, see Genschow et al. 2021).

Importantly, the open science transition is not abrupt but rather a gradual process influenced by trends and technological advances, such as artificial intelligence (AI). AI offers powerful tools to increase confidence in published findings but comes with significant challenges, for example concerning their trustworthiness (Cambria et al. 2023) and their ability to pretend an understanding of facts that stems from linguistic co-occurrences rather than an actual grasp of concepts, their interrelations, and meanings (Cambria et al. 2023; Messeri and Crockett 2024; Tully et al. 2025).

Many publishers are already equipping editors with AI tools to subject manuscripts to an initial quality control by detecting potential errors, plagiarism, or inconsistencies in manuscripts (Kousha and Thelwall 2024). Researchers have also started using AI-powered automation to validate experiments, check for inconsistencies, and ensure that published results are reliable. For example, researchers from the University of Bern and the University of Leipzig recently launched a tool that compares preregistrations to published versions of papers (https://regcheck.app/). Furthermore, Yeykelis et al. (2024) used large language models to generate nearly 20,000 personas that match respondent characteristics to replicate 133 experimental findings from recently published *Journal of Marketing* studies—see also Cui et al. (2025).

However, AI tools can not only be used to analyze research practices and the replicability of findings, but may support researchers across all stages of the research process. For example, AI tools can generate detailed documentation of data processing and analysis steps, facilitating reproducibility and replicability. Indeed, a considerable proportion of early career researchers also use ChatGPT to refine software code (Nordling 2023). On a more generic level, by lowering technical barriers, AI enables researchers from diverse backgrounds to participate in the open science movement. AI-powered tools can translate scientific papers into multiple languages, summarize complex research for broader audiences, and even assist in generating hypotheses or designing experiments (e.g., Banker et al. 2024; Luo et al. 2025), thereby forstering inclusivity. Multiple authors discuss how researchers can collaborate with AI in research projects and what aspects of the research process could be outsourced to AI (e.g., Arora et al. 2024; Sarstedt et al. 2024b; Tomaino et al. 2025; Yoo et al. 2024). Most recently, Tomaino et al. (2025) leveraged AI tools, including Gemini and ChatGPT-4, to assist with various aspects of the research process. The authors conclude that the examined LLMs perform reasonably well in the early stages of a research project (e.g., idea generation, literature summaries, and research design development) but struggle in later stages, particularly in data analysis and interpretation.

While AI offers many advantages, it also presents challenges for open science. AI-generated research must be scrutinized for biases (e.g., Hu et al. 2025; Santurkar et al. 2023), and issues related to intellectual property and data privacy need careful management (Gibney 2024; Heidt 2024). Open-source AI models and algorithms can help mitigate these concerns by promoting transparency and allowing the scientific community to audit and refine AI-generated outputs. An important step in this direction is also the integration of explainable AI for predominantly black box models such as many LLMs (Cambria et al. 2024).

7 Is Business Research Falling Behind? A Call to Action!

As with every good tale, also the tale of open science should spur discussions about its parallels in other disciplines. Business research has not yet experienced a rupture that compares to the replication crisis narrative of the psychological sciences. However, there is no doubt that business research is witnessing what the well-known late author and journalist Roger Willemsen referred to as a “Knacks” (i.e., a crack). Triggered by this crack, the discipline slowly shifts into a new direction. Not everyone may notice this crack until its full impact unfolds. Cracks rarely come with immediate radical changes but induce subtle shifts, only identifiable in hindsight—like Ioannidis’ (2005) or Bem’s (2011) studies.

Currently, business research largely remains an observer of the quests and battles that occur elsewhere. While other disciplines, especially psychology, already witness a triumph of the open science movement, business research is still in the process of finding its position. We, therefore, aim to encourage readers to reflect on the virtues and challenges of open science and to inspire a conscious engagement with the topic, both on the level of the individual researcher, but also on the level of business research as a scientific discipline.

When confronted with the strong dynamics of open science practices and discussions on replicability in psychology (e.g., Baumeister et al. 2023; Fiedler and Trafimow 2024; Isager et al. 2023; Protzko et al. 2024; Vazire 2018), traditional business researchers may be torn between a new more open world and their well-known ways of working and gratification. While we understand this hesitation, there is no way back—the crack is here to stay, and it is unfolding at a rapid pace. Consider, for example, consumer research, where concerns about replication rates have started to emerge in the last decade (e.g., Frederick et al. 2014; Maier et al. 2024; Ruggeri et al. 2020; Verschuere et al. 2018; Yang and Lynn 2014). In response, the field has started adopting open science practices by introducing registered reports (e.g., *International Journal of Research in Marketing, Journal of Consumer Research, Nature Human Behaviour, Psychology & Marketing*), discussing the applicability and merits of open science practices (e.g., on preregistrations, Pham and Oh 2021a, b; Simmons et al. 2021a, b), and introducing editorial policies that foster open science practices (Labroo et al. 2022). These discussions, however, revolve more often around whether to implement open science practices at all or how to micro-dose open science into existing workflows.

In addition, for individual business researchers, the benefits of engaging in open science may often seem less tangible than the initial inconvenience associated with practices like preregistrations. At least this is our experience and an experience that many of our colleagues shared with us. As such, some of us, who met the open science hero describe their first encounter and shift towards open science as initially motivated by external pressures. To illustrate, some turned towards open science because they received significant pushback from reviewers asking to include preregistered studies in the empirical package. Setting up the first preregistration thereby often comes with uncertainties about what it takes to create a "good" preregistration and feelings of unease specifying everything in advance. Some of us may have struggled to recognize the value of preregistering when doing it for the first time and may have perceived preregistrations as a waste of time. However, some preregistrations later, most of us may see how preregistrations help to conduct better research since specifying variables, hypotheses, and analytical approaches in advance forces oneself and one's co-authors to engage deeply with the study beforehand. Some of us realized that this brings research to a new level compared to before, when one might have just briefly discussed a study with one's doctoral students and then just had it run its course.

Based on our own experiences and those shared by our colleagues, we believe that the episode outlined above is not a unique case. Many of us may find it challenging to start with open science—perhaps because we shy away from the effort, cannot yet see or grasp the benefits, or simply do not perceive any added value in it. The episode illustrates how encounters with open science can transform long-standing beliefs, rendering some preconceived notions about open science engagement unrealistic. Advocating for increased open science efforts in business research should, however, not go unnoted by the fact, that many of us might experience uncomfortable internal dialogues when deliberating to venture into this direction.

We encourage engaging in this inner dialogue not only individually in silence but collectively as a discipline so that together we can drive an open science transformation in business research. Following this spirit, we hope that our article will spark debates and reflections on open science among business researchers, be it in conversations with co-authors, PhD students, reviewers, and University boards. Once individualistic efforts become collectivistic action, challenging traditional research approaches, business research as a discipline may create knowledge in fields such as sustainability, digitalization, or entrepreneurship that will endure ever after.

Does this mean that from this day on business research and open science will live in a land of milk and honey? Certainly not! Many questions that come along with open science efforts in business research require answers and guidelines, as detailed previously. Given the diversity of business research as a scientific discipline, there is a plethora of methodological approaches. These range from experimental approaches, over modeling of big data, to qualitative research approaches. While experimental and correlational research as dominant in psychological science may lend itself more suitable for current open science practices such as preregistrations, other approaches like qualitative interviews might seem more difficult to fit in a preregistration template given its typical rather explorative nature. And what about the potential practice of a data-first approach as it may be applied in survey or modeling approaches (Golder et al. 2023)? Here, researchers need to find or develop common ground on how open science can be practiced for different methodological approaches. In line with this notion, we need standards that define the required level of specificity for proper preregistrations that align with these different methodological approaches. And, of course, with the different methodological approaches come different questions about data-sharing policies (e.g., for sensitive qualitative data or company data sets)—see Deer et al. (2025).

If business research as a discipline wants to venture into the direction of open science, we need to foster debates within, but also across business research fields, to form a unified representation and understanding of what open science means to us—not necessarily what open science is, but why it is meaningful for us as a discipline. If it is our aim as a discipline to create a lasting impact, we need to conduct research with reliable findings, which requires exposing ourselves to open science practices.

Clearly, the hardest part here is to change oneself to overcome uncertainties associated with open science practices in one's own research and to understand that doing things differently today does not imply that what we did in the past was "wrong." We should respect our past research for what it is: research that aligned with the methodological zeitgeist of the times back when it was conducted. This implies acknowledging the end of the "past-time paradise," while recognizing that current approaches require adaptation to new standards and perspectives. The winds have changed, and as a discipline, but also as individual researchers, we need to set our sails.

8 Epilogue

The open science journey often brings to the surface a range of doubts and dilemmas, from the demands of preregistration to the vulnerability of opening one's work to new forms of scrutiny. To capture the essence of these experiences, we conclude with a reflective piece in verse:[2]

External pressures paved the way,
A reviewer's pushback came to stay—
"Your methods lack a prereg plan."
Reluctant, yes, but so it began.

[2] This poem created by one of the authors using ChatGPT 4o; suno.ai 3.5 was used to set the poem to music.

But can I? Should I? Do I dare
Let others see what's hidden there?
What if they judge? What if they find
An error buried deep inside?

Preregistration—daunting task,
Laying it out before I ask
The data for its hidden clues,
Before I know the path I'll choose.

But would it sharpen what I seek?
Keep me honest, keep me meek?
Perhaps the rigor's worth the strain,
The guardrails keeping thoughts in lane.

It takes more time, yes, this I know,
To clean, prepare, and let it show.
But in the end, it might just pay
In trust, in growth, another way.

The real question's what I want to be—
A keeper of the status quo, or free?
To move with change, embrace the shift,
And give my work a deeper lift.

And think—what doors might open wide,
If others joined me on this ride?
New eyes, new voices, side by side,
A shared pursuit, a common guide

So maybe I'll start small, just try—
One project where I touch the sky,
Where openness becomes my creed,
And see where all these choices lead.

Alright, tomorrow. Let's begin.
The hardest part? Just diving in.

Musical arrangement: https://suno.com/song/e42d93bb-32b4-4c48-aa83-7dc4d5c310e7.

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