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Why we need a living meta-analysis of self-determination theory: an illustration examining temporal changes in need supportive education

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Abstract
This article introduces the concept of a living meta-analysis, and presents a prototype specific to the field of Self-Determination Theory. This living meta-analysis is proposed to supplement the current journal article-based system of knowledge storage and synthesis, and will (a) increase the consumptive capabilities of researchers (i.e., the amount of research to which one is exposed), (b) minimize cognitive biases that influence scientific knowledge, (c) reduce the file-drawer problem, and (d) create new knowledge through mass synthesis of existing research. We then exemplify a potential use of this recently developed living meta-analysis of Self-Determination Theory by examining whether prevalence of autonomy supportive educational contexts have changed over time, and whether countries display mean differences. We also examine if national level indicators predict these differences. The proposed living meta-analysis and associated norms, much like the recent norm of publicly available data, may be viewed as an industry standard in the near future.

Keywords Self-determination theory · Meta-analysis · Meta-science · Open science · Autonomy support, education

The volume of psychological research is expanding at an exponential rate, and this holds true in the field of Self-Determination Theory as well (Cerasoli, 2023; also see Fig. 1). This trend in psychological research was noted in 1990 by Thorngate who raised serious concerns about how individual researchers will cope with a literature that is growing faster than our ability to consume it. Specifically, Thorngate (1990) predicted that in response to overwhelming amounts of literature, researchers would narrow their focus and specialize in increasingly restricted areas within a discipline. This may create barriers between disciplines or domains, hinder cross-disciplinary communication, and ultimately limit integration of knowledge. Thirty years later, these concerns appear well justified. However, as noted more recently (Nosek & Bar-Anan, 2012), too much information is not a problem in and of itself, but rather the limitation on scientific progress stems from our inability to synthesize and communicate this information in an effective and meaningful manner, particularly through the current scientific journal system. While some have proposed systematic changes to journal administration, peer-review processes, and academic incentive structures (Nosek et al., 2012), proposed here is a structural change to how we store and synthesize research information in the SDT field of research though a large-scale and publicly available database (Bosco et al., 2015; Elliott et al., 2017; Sakaluk et al., 2023; Spadaro et al., 2022).

A centralized database such as this may be particularly useful to the SDT field of research given SDTs application across a broad array of different life domains, in countries around the world, and given the critical mass of research findings that are being published each year (Cerasoli, 2023). Additionally, there remain key propositions of SDT that can be further examined through large meta-analytic datasets such as this, including its universality hypothesis (the proposition that basic psychological needs are universal and apply across all cultures and contexts), which can be difficult to test with smaller databases or primary research.

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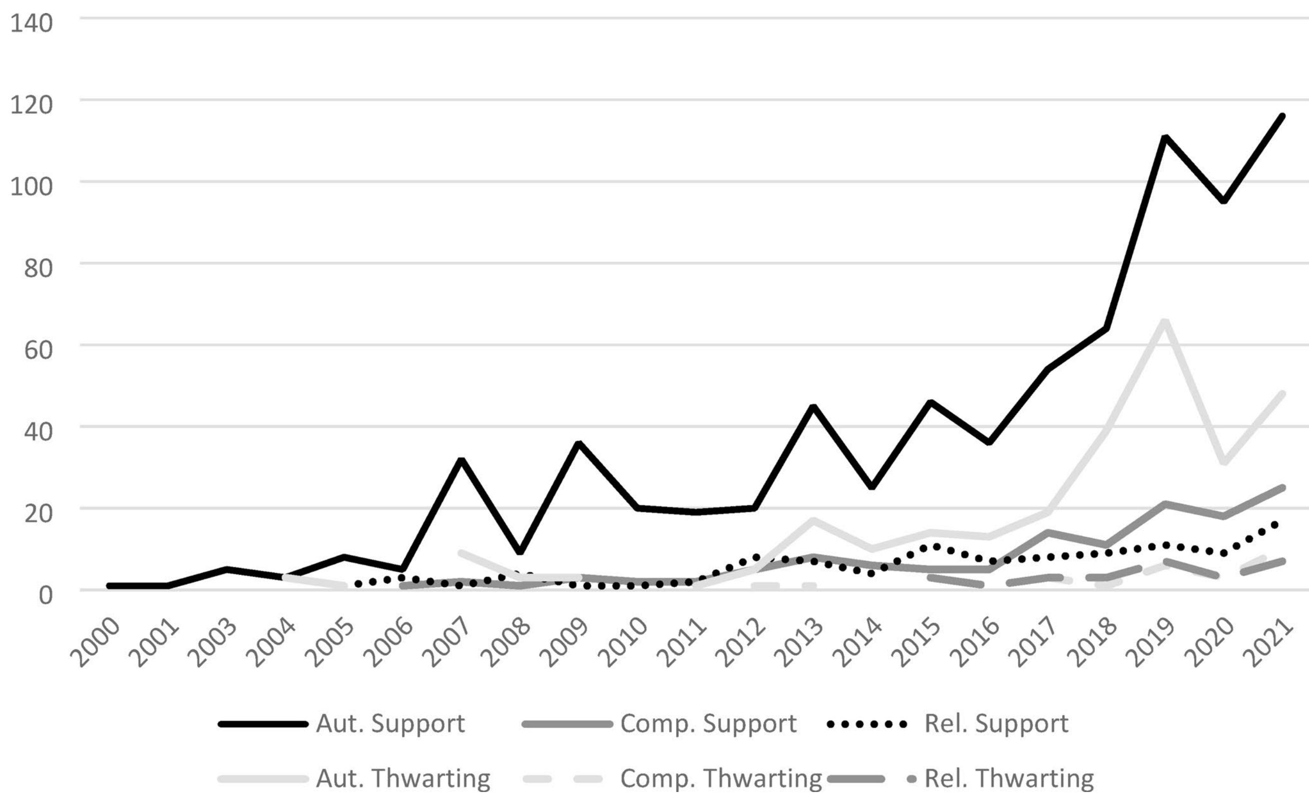

Fig. 1 Number of new effects published for each support/thwarting variable by year

As exemplified later in the article, there are also opportunities to examine novel research questions. In this article, we first outline why we need better systems to collate findings within the SDT field, before introducing our database of SDT data as it currently stands. We then provide an example of how this database can be used by examining whether autonomy-supportive practices in educational contexts have changed over time, and whether they differ by country. This approach to data synthesis may become an established norm similar to the recent move towards publicly available data.

Current approaches to knowledge compilation and synthesis

The purpose of academic journals is to house research findings so that future scholars can access this information and synthesize it into a coherent and accurate sum of knowledge. This method of knowledge storage has existed for nearly 400 years and while it has expanded, it has not substantially adapted over that time. In order to gain an understanding of a topic, a researcher may have to read hundreds of articles, before integrating this information with their knowledge of previous research, forming an overall impression of a topic area. This raises obvious problems. First, being exposed to the entirety of an ever-expanding research literature has become an impossibility. As pertinently noted by Thorngate in 1990, "information tends to proliferate, but attention does not." This is a fundamental flaw in the purely text-based journal system and represents a serious concern by itself.

Secondly, this system does not account for the well-known limitations of human information processing and decision making (e.g., Hills, 2019; Kahneman & Klein, 2009). Specifically, it must be acknowledged that individual researchers are left to synthesize information gathered from across many research papers. However, unusual, attention-grabbing, and negatively valanced effects will often be given more weight than less interesting but no less valid effects (Hills, 2019; Nosek et al., 2012). Rapidly growing literatures also give rise to other concerns, including disproportionate prominence being awarded to established scholars (the Matthew effect; Merton, 1968, 1988), or a preference for studies with catchy titles (Adair & Vohra, 2003; Thorngate, 1990). This is to say nothing of the more malicious errors such as attending only to research that supports the researcher's preconceived ideas (Antonakis, 2017; Hills, 2019). A well-functioning discipline of scientific study should minimize these types of biases to the greatest extent possible and strive for objectivity. However, with the expanding wealth of research being produced each year, cognitive shortcuts will increasingly be applied as proxy measures of quality (Thorngate, 1990). This centralizes power and influence within a select few and thereby amplifies the impact of cognitive biases to the detriment of scientific progress. The exponential growth of research is straining this system which in turn is becoming increasingly insufficient and gradually failing to provide the common pool of shared knowledge necessary for communication (Gendreau, 2002; Thorngate, 1990). As such, we may look to supplementary models of knowledge storage and synthesis that can be adopted to better serve SDT scholars and the psychological sciences more generally.

Traditional meta-analyses are increasingly relied upon to synthesize large amounts of data - this is indeed a key strength of meta-analysis. However, even this method of synthesizing information has limitations that become more pronounced at larger scales. For one thing, traditional meta-analyses are temporally stagnant and begin to age as soon as the literature search is complete. Updating or adding new information to traditional meta-analyses can only be done if the coded data are shared, and even then, missing information (e.g. uncoded effect sizes or moderator data) will often require substantial re-coding and substantial inconvenience. This is exacerbated when different meta-analyses require different search parameters. As a result, almost all meta-analyses are conducted anew rather than building on past work, resulting in literatures being repeatedly searched and coded by different groups, and substantially duplication of efforts. Given how quickly academic research, and SDT research in particular, is growing (Cerasoli, 2023), meta-analyses will be conducted more frequently and will require increasingly large datasets (see Ryan et al., 2022), resulting in ever increasing investments of time and effort. This becomes highly inefficient and more so as the literature continues to grow. As such, meta-analytic procedures need to develop (Cuijpers et al., 2022).

Living meta-analysis

The proposed solution to these issues is simple in principle: all research findings and study metadata from SDT studies are entered into a centralized and publicly available database. This study-level data can then underpin largescale meta-analyses through a publicly available meta-analytic platform (see metaBUS and CoDa for similar, though different examples; Bosco et al., 2015; Spadaro et al., 2022). By coding detailed study information such as effect sizes, sample sizes, time lags, and sample characteristics into a centralized database, we can develop a database containing all possible research findings on SDT-related topics that can be explored and analyzed freely. As such, all researchers will have access to not only a complete list of findings on any given focal topic, but also the ability to run large-scale, nuanced, and perpetually updated meta-analyses based upon an entire field of research, without spending years collecting this data oneself. All research using standardized measures and/or interventions would be viable inclusions, meaning that such a system could integrate findings from across many topic areas across different areas of psychology, including but not limited to management and industrial/organization psychology, education, sport and exercise, and developmental psychology, clinical psychology and social psychology generally. New research findings will therefore add knowledge through published research articles, and also combine with previous findings in an integrated and live repository, allowing for efficient syntheses of the collective efforts of thousands of researchers. Such a method would increase the consumptive capacity of researchers (Thorngate, 1990).

This idea is not entirely new, having been explored in different capacities previously. For instance, Tsuji and colleagues (2014) introduced the concept of Community Augmented Meta-Analyses (CAMA), and Braver et al. (2014) concurrently discussed the notion of continuously cumulating meta-analysis (CCMA). More recently, Cuijpers et al. (2022) introduced what they call meta-analytical research domains (MARD), while Sakaluk et al. (2023) described cumulative, dynamic, and accessible syntheses (CDA). Further, Elliot and colleagues (2017) introduced the concept of living systematic reviews. All have a shared goal of developing methods for continually updating our shared knowledge of a given field. While the living meta-analysis (LMA) proposed here shares this goal, it also takes a broader and more inclusive approach by providing a platform that moves beyond updating individual meta-analyses, and instead aims to encompass the entire field of SDT research.

Living meta-analysis can supplicate the academic journal model through several substantial contributions, including (a) improving the specificity and efficiency of research by helping to address the information scaling problem, (b) minimizing judgment errors, (c) combatting file-draw problems that contributed to the replication crisis, and (d) contributing new knowledge through powerful meta-analytic integration of past findings. We expand on these points below.

First, this approach will allow researchers to be exposed to findings from substantially more research. Not only will this improve the efficiency of literature reviewing, but it will also help standardize a collective understanding of a given topic, providing a common and comprehensive basis of knowledge (Nosek & Bar-Anan, 2012; Thorngate, 1990). This clear understanding of what is known, and by extension, what remains unknown about a topic, will increase both the efficiency and precision of future research. For example, a researcher may aim to uncover additional mediators or moderators that influence the relationship between any two variables. Rather than combing the entire published literature across any number of potentially related disciplines, this researcher may instead access the proposed database system, specify the model they wish to test, and have all relevant data retrieved and meta-analyzed in a matter of minutes. The individual studies used to estimate this meta-analytic result would be listed and, if desired, can be inspected in detail. Additionally, this meta-analytic system will better enable the incorporation of control variables and competing variables (i.e., other known influences), thereby reducing the influence of bias by omission (Antonakis, 2017). Complex analyses involving a large range of confounding or competing variables will be possible as the database grows and power becomes more substantial. As such, this will prove as useful for editors and reviewers as it will for researchers planning their own work.

A centralized and open access database of findings will not only increase the rate at which researchers absorb scientific information (i.e., consumptive efficiency; Thorngate, 1990), but will also scale alongside the exponentially growing literature to become more powerful as further findings are included (see Linden & Hönekopp, 2021 for a relevant discussion of heterogeneity in meta-analysis). That is, the power and precision of results will continue to improve as more data is added over time, and the range of competing hypotheses, control variables, and moderation effects that can be examined will likewise continue to increase. In this respect, this approach not only addresses the scaling problem but seeks to capitalize on it.

Second, this data-centric approach to knowledge storage and synthesis helps overcome situations in which human error and bias influence the knowledge synthesis process. Results are presented side by side regardless of author reputation or affiliation, and weighting could be given based upon sample characteristics indicative of high-quality data (e.g., study design and sample size) as is common in meta-analysis. More subtle factors such as quality of writing or how recently it was viewed are also controlled. Moreover, the readily available summary of findings that will be accessible to editors and reviewers makes it more challenging to defend more pernicious effects such as selective attention. While not completely free form human error, given the demonstrated ability of algorithmic decision making to outperform intuitive decision making (Grove et al., 2000), this approach appears promising.

Importantly, this living meta-analysis stands to capture non-significant findings in a manner that journal publications do not. Specifically, results that have been historically less attractive to journals, such as non-significant results and replication efforts, can still be included in this database system. In this way, such an approach to data storage and synthesis can substantially alleviate the file-draw problem. Nonreplicable or unusual results will influence the direction of a literature to a far lesser extent as they will be displayed alongside all remaining results regardless of how attractive or counter-intuitive the result is (Nosek et al., 2012). As such, rather than methodological approaches (Shrout & Rodgers, 2018), or systematic changes to the peer-review and academic incentive systems (Nosek et al., 2012; Suls & Martin, 2009), this approach will help provide a systematic organizational solution to help alleviate the replication crisis, at least within some areas of psychological science.

Finally, this approach stands to contribute substantial new knowledge though the meta-analytic integration of vast amounts of data. As in any good meta-analysis, the result of integration is greater than the sum of its parts. This is because effects that cannot be identified within primary studies are made visible when examined across studies. For example, the examination of heterogeneity (i.e., moderators such as context, culture, age, change over time) is a key role of meta-analysis (Linden & Hönekopp, 2021). While difficult to achieve in primary studies and even many smaller meta-analyses due to power constraints, meta-analyses based upon the full wealth of relevant research would be less likely to suffer such limitations. With time and widespread use, the living meta-analysis will lend itself to more advanced applications such as meta-science research, helping to improve and integrate psychological theories (Jamieson & Pexman, 2020), searching for big pictures (Reed, 2020), and exploring societally relevant issues.

Open science

The Open Science Movement will likely be an essential catalyst enabling the move towards large-scale data integration. This movement was initiated to improve transparency and availability of scientific research, and it provides an ideal and necessary context through which to introduce new norms around the reporting of data and findings. Recent open science initiatives such as the Open Science Collaboration (2015), the Many Labs studies (Klein et al., 2018), and the Psychological Science Accelerator (Moshontz et al., 2018) provide precedence for this type of horizontally integrated system (Uhlmann et al., 2019). However, while these past projects represent task groups set up for the purpose of conducting a study, the system proposed here is more pervasive and extends participation (and rewards) to all researchers in perpetuity. As such, the system not only aligns with the Open Science principles put forward by Nosek and Bar-Anan (2012), but also extends this to encompasses truly horizontal participation (Uhlmann et al., 2019). In doing so, this maximizes the value of collected data, increases our ability to consume more research (Thorngate, 1990), and in doing so will fast-track the discovery of new knowledge.

There have been previous similar efforts that align with this model of knowledge storage and synthesis, specifically, the metaBUS project (Bosco et al., 2015). MetaBUS was a pioneering prototype from the discipline of Management research that shares many of the same goals as the proposed model of knowledge storage and synthesis. This database went live in 2015 and boasted an impressive collection of over one million effects, making it remarkably advanced for its time. However, two major differences need to be highlighted. First, metaBUS limited its scope to highly regarded management and applied psychology journals and did not integrate findings from less prestigious journals or from unpublished and unpublishable studies (Fanelli, 2012; Ferguson & Heene, 2012). A disadvantage of this approach is that the systematic selection of data will likely exacerbate both the file-drawer effect (Nosek & Bar-Anan, 2012; Rosenthal, 1979) as well as reinforces the notion of accumulated advantage (i.e., "the rich getting richer", Merton, 1968, 1988), which may not align with scientific ideals. Second, and more fundamentally, metaBUS was a vertically integrated project (Uhlmann et al., 2019) that relied on AI scraping of publications and further coding by research assistants periodically hired by the database administrators. While this approach is practical and understandably necessary at the time, the reliance on vertical rather than horizontal integration limited the capability of MetaBUS to record breadth and depth of knowledge (Thorngate, 1990).

The LMA proposed here aims to overcome some of these challenges and provide much greater depth of knowledge by focusing more precisely on the SDT field of research, and by capitalizing on horizontal integration made possible by open science practices and our community of scholars.

Implementation and data collection

The proposed living meta-analysis of SDT consists of three primary parts: (1) the database itself including taxonomic structuring, (2) an online platform through which to interact with the database and, (3) a means of imputing new coded data. Fortunately, the current prototype includes the first two features in operation, and the third in development.

Maintaining a database can be as simple as compiling data in an excel file– a process most meta-analysts will be familiar with. However, as the scale of data increases and additional functionalities are added, a more sophisticated system will be required. Currently the living meta-analysis of SDT is housed on the HubMeta platform (Steel et al., 2023). This is a platform designed to assist in conducting literature reviews and meta-analyses with built-in functions for deduplication, screening, coding, and analysis capabilities. It provides not only a database function, including a hierarchical taxonomy of variables, but also provides the two remaining functions for data entry and analysis.

Viewing the living meta-analysis via HubMeta is relatively straightforward. A publicly available version of the database is currently available on HubMeta in a view-only format. The platform also enables analyses. The "filter" function can be used to restrict the search to relevant data (such as specific life domains, countries, study designs, or publication statuses), before selecting the variables of interest. The query will then be sent to an R server to calculate the results which are then returned via the platform in typically about 1–2 min. While new analytic features will be developed over time (e.g., MASEM and analysis of means), this analysis feature is already functional. Additionally, the data from the database can be downloaded from the HubMeta platform for use in more complex analyses.

The final piece of infrastructure will be the ability to introduce new data to the database. Given the abovementioned proliferation of research, we anticipate that this will be the most challenging step. The database currently includes data from several large-scale meta-analyses published on SDT topics in recent years, specifically, Bradshaw et al. (2023), Bureau et al. (2022)., Howard et al. (2017, 2021, 2024), Mossman et al. (2022), Slemp et al. (2018, 2024), and Van den Broeck et al. (2021), combining to provide approximately 30,000 cumulative effect sizes from over 2000 articles. Data from other meta-analyses (i.e., Curran et al., 2015; Hagger & Hamilton, 2021; Li et al., 2013; Ng et al., 2012; Okada, 2023) have been obtained and will be imported to the database in time, while other remaining meta-analyses (see Ryan et al., 2024) can be coded subsequently. Lastly, we are actively pursuing several new meta-analytic investigations which will also added substantial amounts of data in due course.

While these developments are promising, two issues remain. First, there remains large amounts of relevant data from existing primary research that has not been collected or coded yet for meta-analysis, and therefore, is not incorporated into the database. Capturing this information will require ongoing efforts in the coming years, likely requiring a coordinated effort to ensure all areas of the SDT literature are included. However, given the finite number of studies currently in existence, this is a surmountable task.

The second and more pressing issue is the influx of data that will be published in the future, which will require a more innovate and scalable solution. Artificial intelligence has been considered to solve, or at least help with this problem (Bosco et al., 2015; Banks et al., 2018), and will undoubtedly be an important presence in the future. As yet there are no AI functions that are able to successfully complete key steps in the process (e.g., identifying relevant studies, labelling variables correctly, or extracting relevant effect size and study characteristic data). Tools exist to assist in some of these functions, yet human input currently remains necessary. An AI function that can effectively complete searches and coding will be a welcome development that we expect to see in the coming years. However, in the meantime we aim to populate the database via coordinated effort and with the help of primary researchers themselves. Specifically, we propose that researchers will be able to directly add their results and study information to the database by coding a correlation matrix and associated study data to the database via a webpage.

In other words, the meta-analytic database described here will be decentralized, or horizontally integrated (Uhlmann et al., 2019) to the greatest extent possible, such that the researchers who conduct primary research will upload the majority of the data themselves, as opposed to relying on a dedicated team to search, manage, and code the data as happens in vertically integrated systems. This may be a necessary intermediate step to deal the scaling problem until AI can maintain the database itself. If studies are coded by the researchers who collected and analyzed the data, the number of contributors will scale in proportion to the number of articles being published, thereby providing a more sustainable system.

While this may sound onerous, most samples take approximately 15–20 min to code, with only one member of a research team needing to do this. Although we recognize that scholars already face enormous auxiliary responsibilities alongside teaching and publishing, we firmly believe that the development of such a database will yield substantial returns for the SDT community (Sakaluk et al., 2023). Community uploading of data is not currently possible in the HubMeta platform, but the necessary webpages to achieve this data entry are currently being developed and reconfigured to facilitate this process.

In summary, our method of data collection is twofold. On the one hand, our team of meta-analysts is seeking to capture existing studies. Concurrently, we aspire to facilitate the direct submission of newly collected datasets by primary researchers, streamlining the integration process. The combination of these two methods, augmented by AI wherever possible, should be sufficient to eventually capture the entire field of empirical SDT research overtime.

Considerations and limitations

Maintaining data quality. Perhaps the most pressing concern will be the assurance of data quality, particularly when coding is completed by a variety of community members and with varying degrees of AI assistance. While data entry errors are not new in meta-analytic investigations and, due to their random nature, do not systematically bias results (Schmidt, 2015), it is to the benefit of everyone to minimize them wherever possible. The HubMeta platform itself lends itself to higher quality data entry as each study is given an individual page with all data laid out in a uniform and transparent manner. The HubMeta platform also includes safeguards against data errors, for example by highlighting out of range values and showing error warning when attempting to save out of range values. Functions such as this will be extremely helpful to reduce errors in coding. While the current view-only version does not permit changes to the data by the public, we are developing a function to allow users to report errors that can then be addressed by the administrating team. Adding new data to the database, as discussed above, will require additional quality checks as well. To capture potential errors, newly imputed data will need to be held for verification, before being added to the database proper. The precise verification procedure is yet to be determined, but will likely involve AI checking of submitted data against a published article or pre-print in conjunction with brief manual checking by an administrator.

Peer review*, *pre-prints*, *and publication bias. Another pressing issue is determining when datasets should be deemed eligible for inclusion. A simple solution would be to only code data that has passed through peer review and is published in an academic journal. However, such an approach would have implications for publication bias. Publication bias, also known as the file-draw effect, occurs when significant findings are more likely to be published than non-significant findings. As a result, published literature can be biased towards larger, and therefore more significant effects. To combat this, meta-analysts often strive to collect unpublished data (so called grey literature), such as data from dissertations, conference presentations, technical or policy reports, and other forms of unpublished data that may exist in the metaphorical "file-draws" of researchers working in the field. This is often done via announcements on list-servs and direct contact with researchers.

An alternate approach would be to include any data without requiring publication. While such an approach would help counter publication bias and would likely be used responsibly in the vast majority of cases, it would be vulnerable to manipulation if, for example, someone to enter large amounts of false effects. Such an occurrence, though unlikely, would be detrimental and therefore this is not a viable solution. One compromise would be to accept data from any study that has at least a pre-print (or pre-registration) describing the study design and methodology. This approach would capture dissertations from research students, conference proceedings and book chapters, as well as data that has been prepared for publication but may never get there. While the exact procedures for data imputation are still being finalized for this LMA, we believe a solution such as this may be optimal.

Ethics of data collection. Currently, we are only gathering study-level summary data that are required for meta-analysis, such as effect sizes, study characteristics, sample demographic information, and associated meta-data (e.g., reference information). Because this system collects study-level summary data rather than individual participant data, it does not breach the informed consent that individual participants provided regarding future storage and sharing of their individual data. It also does not breach privacy obligations since the summary data is not attached to individual participants and therefore cannot identify individuals. If the system were to accommodate primary data from individual participants, this would raise such ethical concerns. For now, this is not a part of its functionality.

The proposed system, with its focus on study-level summary data, is still limited regarding copyright and the presentation of study PDFs alongside the coded data. Ideally, each entry in the database could be accompanied by a PDF of the article from which it was drawn. This would make it particularly easy for users to engage with the research beyond the statistics, and especially for those outside of a university system who have limited access to academic journals. However, providing these PDFs would often violate copyright. As such, the database does not currently provide PDF versions of the articles, though could easily be made to do so if/when academic articles are made open access. With recent trends towards open access publishing agreements, we expect that copyright will become less of an issue in the future.

Theory and the academic journal system. The traditional model of knowledge storage based on academic journals will continue to be important as detailing the procedures of a study and theorizing about findings remains an essential aspect of any psychological science. Open source meta-analysis does not advocate for empiricism or undermine the importance of theory in psychological sciences. Theory remains the guiding framework through which empirical data need to be viewed in order to infer meaning. Likewise, this proposal does not excuse or undermine the value of rigorous study design (Anderson et al., 2019; Baumeister et al., 2007). Instead, as all relevant study characteristics are coded, results can be weighted based upon qualities of the data, or analysis parameters can be set to examine, for example, time separated data, intervention studies, or published vs. unpublished studies if these alone are pertinent to the researcher's question. The proposed infrastructure simply provides consolidation and clarity of what the field knows about a topic and, when used effectively, can preemptively and efficiently answer questions, scaling alongside and capitalizing upon the growing literature.

Exemplifying the uses of the SDT living meta-analysis

Is the level of need support/thwarting in education institutions changing over time?

In this section we present a series of analyses using the living meta-analysis of SDT as it currently exists. This is only one application of the LMA among many possibilities. This example simply serves to highlight how a large meta-analysis, that may ordinarily take 1–2 years from data collection to analysis, can now be completed in just a couple of months with a small team. As the amount of stored data increases, the time taken to compile a novel meta-analysis will continue to fall, while the power of analyses will scale up.

Current knowledge supports the claim that students perform well and experience wellbeing when receiving autonomy support in educational contexts, and much of this can be attributed to basic psychological need satisfaction and more autonomous forms of motivation (Bureau et al., 2022; Guay, 2022; Howard et al., 2024; Okada, 2023; Reeve & Cheon, 2021). However, despite the substantial amount of research in this area, we do not know clearly if educational institutions, and particularly teachers, are adopting more autonomy-supportive practices over time. Given how beneficial need support appears to be for student outcomes, we would hope that need-supportive practices are becoming more common over time. However, it is also possible that as educational institutions become more competitive (with education increasingly commodified), less humanistic or student-centered practices may in fact be encouraged (Ryan & Weinstein, 2009; Yu et al., 2018). In practice, we do not know whether educational contexts are becoming more supportive of student needs over time. Additionally, while evidence has indicated that basic psychological needs and need supportive behaviors are associated with positive outcomes across many countries (e.g. Chirkov et al., 2003; King et al., 2024; Martela et al., 2023; Slemp et al., 2024), it may be useful to further document whether, and to what extent, need supportive practices are indeed present across different countries, and whether differences are impacted by economic or social factors. Thus, building on recent efforts to meta-analyze SDT in educational contexts (Howard et al., 2021, 2024; Slemp et al., 2024; Vasconcellos et al., 2020), we conduct a series of exploratory analyses to address the following questions, based on existing data, and to demonstrate one use-case for the living meta-analysis of SDT:

RQ1: *Is the level of need support in educational contexts changing over time globally?*

RQ2: *Are there mean level differences between countries in their tendency to create autonomy supportive or thwarting educational contexts?*

RQ3: *Are national levels of need support in educational contexts changing over time?*

Additionally, we may align these differences with country level indicators such as national values (Hofstede, 2001) and gross domestic product (GDP) to explore whether these underlying factors correlate with the different mean levels of autonomy support. We therefore pose two further research questions:

RQ4: *Do national cultural values (Hofstede's values) explain variance in national mean differences?*

RQ5: *Do national level economic indicators (a) GDP/capita or (b) government spending on education (% of GDP), explain variance in national mean differences?*

Data and analyses

The primary research required to answer these questions has already been compiled by Howard et al. (2024) and Slemp et al. (2024), so we can be confident that the list of education-focused studies analyzed in these relevant meta-analyses will be relevant to this study as well. We then coded additional missing information for each of these studies, specifically, (a) mean scores, (b) standard deviation associated with mean scores, and (c) scale ranges for each variable. While we have evidence to suggest that autonomy support scales are invariant across different counties (Hagger et al., 2007), it is important to note that invariance has not been tested or established for all scales included in the current meta-analysis. Thus, we position our work here as preliminary, and future research should seek to model each scale separately or establish invariance of all scales included in such analyses. We also completed coding of moderators when missing in the original coding from Howard and colleagues (2024). The HubMeta platform was used for study coding. Data on national level cultural values were sourced from the Culture Factor Group website, while economic data (GDP/capita and government spending of education [% of GDP]) were sourced from the World Bank Group. The full database used to conduct these studies is openly available via OSF (https://osf.io/273us/?view_only=15d862fb0a3f4b49bcb055baafde36c5), and the full SDT database is available via HubMeta.

The sample therefore consisted of 541 samples from 459 articles. The average age of participants was 16.40 years, and were on average 54.59% female. In total, 71.7% of samples were from cross-sectional designs, 22.8% from time-separated designs, 3.7% from experimental and intervention designs, and 1.8% from diary studies. The average date of publication was approximately February, 2016, with a standard deviation of 4.6 years. However, as displayed in Fig. 1, the number of new effects added to the literature is skewed with the majority of data coming from more recent years. Furthermore, the number of effects relating to competence thwarting and relatedness thwarting remain minimal, making it difficult to analyze these variables effectively. There has been sufficient research on competence support, relatedness support, and autonomy thwarting to analyze, although not as extensive as the research on autonomy support.

All analyses were conducted via the Metafor package (Viechtbauer, 2010) in R Software version 4.3.0 (R Core Team, 2023; syntax provided in the supplementary OSF documents). As mean scores were recorded on different scales with a varying range of points, the means needed to be standardized before analysis. To achieve this, we converted all mean scores onto a 0–1 scale indicating the percentage of agreement reported within each study with the formula y_i = (mean– minimum) / (maximum– minimum), and adjusted the standard deviations to match. We used the "aggregate" command in R to deal with non-independent effects, as happens when a single sample provides multiple indicators of autonomy support and therefore multiple non-independent mean estimates.

To answer the research questions, a meta-analysis of mean scores was conducted on the autonomy support variable. Neighboring constructs such as competence support, relatedness support, and the need thwarting behavior categories were included where possible, but typically had fewer data points and often had not been studied over a long enough period of time for some analyses. To answer RQ1, meta-regression was then conducted to examine if the year of data collection significantly moderated the meta-analytic estimate (year of publication was used as a proxy for year of data collection). Secondly, we used subgroup analysis to examine each country independently (RQ2) before also applying meta-regression by year of publication to each country, answering RQ3. While mean scores were estimated for a range of countries, changes in time could only be calculated for countries from which significant amounts of data have been collected over a suitable period of time. For mean estimates, we decided that at least 5 datapoints were required per estimated effect, while for moderation analyses, where more power is required, we decided that 15 or more samples were ideal, though cautiously examined and interpreted effects including 9 or more samples when concentrated within a narrower timeframe. Sensitivity analyses indicated that removing early (2000–2004) or late studies (2022) did not influence the overall mean estimates or trend over time (see Table S1 of the supplementary materials).

Finally, we examined several national-level indicators that may partly explain the differences in educational approaches recorded in different countries via meta-regression. We first entered the six national values indicators as predictors of national autonomy support, competence support, relatedness support, and autonomy thwarting, before

Table 1 Global mean scores for support and thwarting variables in the educational context

	k	Mean	S.E.	CI 95%		Tau	I^2 (%)
				Lower	Upper		
Aut. support	509	0.630	0.0052	0.619	0.640	0.1168	99.86
Aut. thwarting	183	0.335	0.0100	0.315	0.354	0.1342	99.61
Comp. support	104	0.650	0.0116	0.627	0.673	0.1174	99.94
Comp. thwarting	24	0.252	0.0275	0.198	0.306	0.1335	99.78
Rel. support	88	0.696	0.0132	0.670	0.722	0.1226	99.95
Rel. thwarting	33	0.216	0.0221	0.173	0.259	0.1268	99.86

Table 2 Meta-regression of year of publication on mean support and thwarting scores

Variable	*k*	*b*	S.E.	*p*	CI 95%		I^2 (%)	R^2 (%)
					Lower	Upper		
Aut. support	509	0.0044	0.0011	<0.001*	0.0022	0.0066	99.82	2.84
Aut. thwarting	183	−0.0009	0.0029	0.750	−0.0065	0.0047	99.61	0
Comp. support	104	0.0046	0.0030	0.124	−0.0012	0.0104	99.87	1.25
Comp. Thwarting	24	0.0102	0.0099	0.306	−0.0093	0.0297	99.78	0.18
Rel. support	88	0.0036	0.0031	0.245	−0.0024	0.0096	99.88	0.42
Rel. thwarting	33	−0.0096	0.0066	0.146	−0.0227	0.0034	99.81	3.28

then examining the two economic indicators as predictors of these same variables.

Results

We first examined the global levels of the three support variables and the three thwarting variables. As displayed in Table 1, the global mean score for autonomy support was 0.629 (95% CI 0.619–0.639), indicating that students on average reported 63% agreement with items measuring autonomy support. When converted to a 7-point scale as typically used in primary research, this would equate to a mean score of 4.40. Relatedness support was reported to be just as high with a mean score of 0.696 (95% CI 0.670–0.722), while competence support was estimated at 0.650 (95% CI 0.627–0.672). Mean autonomy thwarting was estimated at 0.334 (95% CI 0.315–0.354). Competence thwarting and relatedness thwarting were estimated at 0.252 (95% CI 0.198–0.306) and 0.216 (95% CI 0.172–0.259) respectively. Heterogeneity statistics, in particular I^2, indicate that there is substantial heterogeneity within the estimates that should be attributable to moderators.

Meta-regression with "year of publication" as the predictor indicated that autonomy support was significantly increasing over time (b = 0.0044, p = < 0.001, k = 509) (Table 2). This indicates that students in educational contexts are reporting approximately 0.44% more autonomy support each year. Given studies in this analysis range across 22 years from 2000 to 2022, we can estimate that global levels of autonomy support may have increased approximately 9.68% over this timespan. Competence support and relatedness support both recorded positive estimates (0.0046 & 0.0036 respectively) but were not statistically significant. This may be because fewer datapoints were available for these estimates (k = 104 & 88), with most studies emerging in the last few years. Likewise, the estimate for autonomy thwarting was negative but not statistically significant (b = −0.0009, *p* = .750, k = 183) as was relatedness thwarting (b = −0.0096, *p* = .146, k = 33), while competence thwarting was positive but not significant (b = 0.010, *p* = .306, k = 24). Figure 2 presents the levels of autonomy support reported globally for each year.

Next, we examined the mean levels reported with each participating country (RQ2). Estimates of mean autonomy support levels were calculated for 21 different countries, as reported in Table 3; Fig. 3. While the error bars remain quite large for several countries, we can be confident that some countries report higher mean levels of autonomy support than others. Turkey, while based on only 9 samples, reported the highest level of autonomy support and confidence intervals distinguish it from all but a few other countries. Canada (k = 37), China, (k = 57), and Italy (k = 17) also have relatively high levels of support compared to other countries. Analysis of competence support and relatedness support were more limited (see Tables 4 and 5) with only six countries to compare for each. These results did not demonstrate substantial differences between countries, due either to a lack of power, or inherent heterogeneity in the estimates, resulting in wide confidence intervals. It can be noted, however, that relatedness support levels from these countries tend to be higher than reported levels of either autonomy support or competence support.

Autonomy thwarting means were also examined and are presented in Table 6; Fig. 4. Interestingly, reports from China were the highest on average (k = 20), followed by France

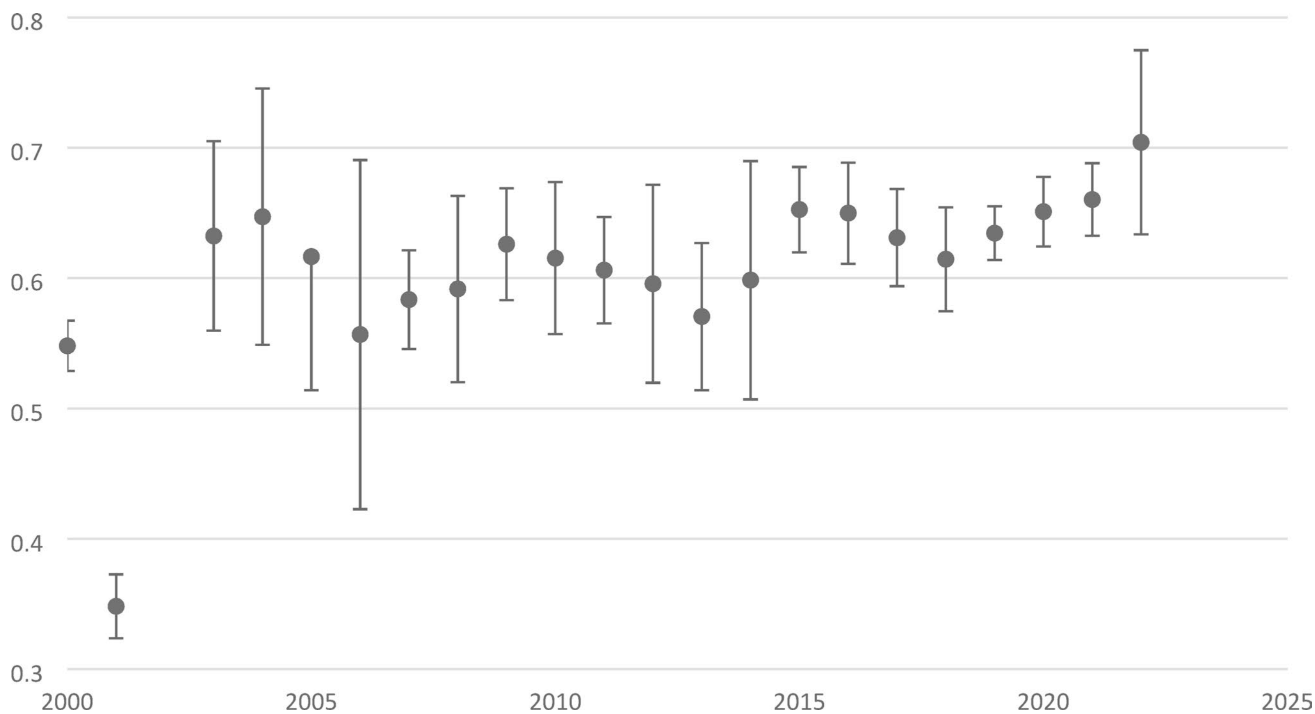

Fig. 2 Autonomy support reported globally by year. On average, data were collected approximately two years earlier than the publication date

Table 3 Autonomy support means by country

Country	*k*	Mean	S.E.	CI 95%		Tau	I^2 (%)
				Lower	Upper		
United States	99	0.633	0.0128	0.6083	0.6585	0.1268	99.75
China	57	0.662	0.0128	0.6372	0.6872	0.0958	99.47
Belgium	42	0.613	0.0247	0.5645	0.6612	0.1593	99.72
Spain	41	0.624	0.0133	0.5974	0.6496	0.0847	99.19
Canada	37	0.669	0.0185	0.6327	0.7052	0.1114	99.73
United Kingdom	24	0.578	0.0139	0.5508	0.6054	0.0672	97.63
Italy	17	0.673	0.0238	0.6262	0.7194	0.0883	98.44
Netherlands	11	0.657	0.0285	0.6015	0.7134	0.0944	99.43
Israel	16	0.634	0.0290	0.5769	0.6907	0.1151	99.23
South Korea	16	0.611	0.0242	0.5633	0.6581	0.0962	99.52
Germany	12	0.533	0.0362	0.4620	0.6038	0.1245	99.86
Greece	12	0.637	0.0171	0.6039	0.6708	0.0576	95.89
Estonia	9	0.647	0.0183	0.6107	0.6824	0.0538	97.10
Turkey	9	0.715	0.0251	0.6655	0.7640	0.0744	98.79
France	9	0.622	0.0409	0.5415	0.7018	0.1164	98.88
Norway	9	0.575	0.0466	0.4838	0.6664	0.1392	99.58
Austria	8	0.610	0.0198	0.5710	0.6487	0.0553	97.57
Finland	8	0.690	0.0308	0.6300	0.7506	0.0865	99.33
Singapore	7	0.609	0.0147	0.5802	0.6378	0.0380	97.10
Australia	6	0.668	0.0495	0.5711	0.7651	0.1205	99.17
Taiwan	5	0.538	0.0320	0.4747	0.6003	0.0710	98.24

(k = 6), South Korea (k = 10), and the United States (k = 20). Profiles describing the combined results from the five most reported on countries are presented in Fig. 5. Finally, it is worth noting that each of these estimates contained substantial heterogeneity, suggesting that student experiences will vary substantially within countries, which may be explained by further moderators.

Research Question 3 was addressed by examining whether “year of publication” was a significant moderator of the mean levels reported within countries. We examined this

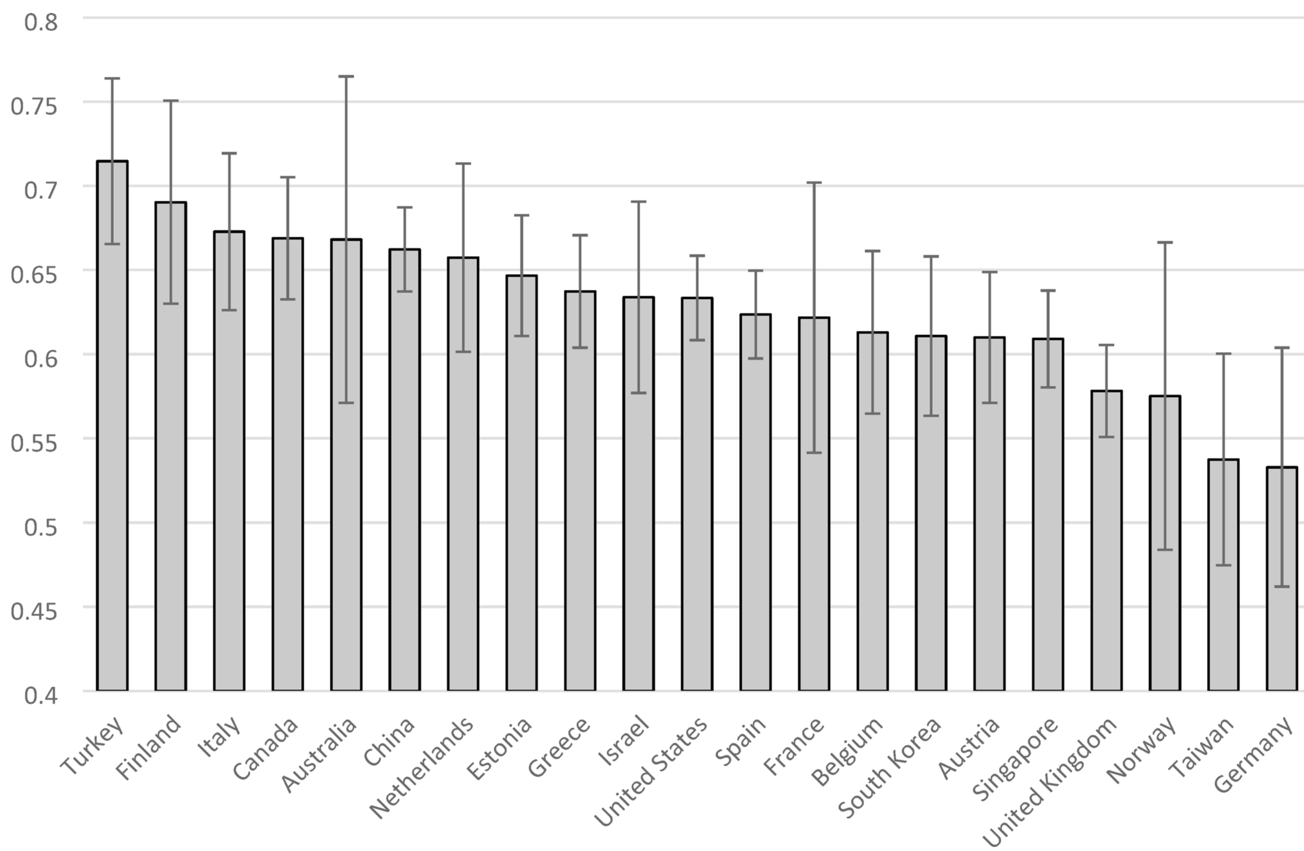

Fig. 3 Mean estimates of autonomy support by country

Table 4 Competence support means by country

Country	*k*	Mean	S.E.	CI 95%		Tau	I^2 (%)
				Lower	Upper		
United States	23	0.645	0.0232	0.5993	0.6901	0.1101	99.76
Belgium	21	0.648	0.0260	0.5967	0.6987	0.1186	99.55
Spain	9	0.689	0.0362	0.6181	0.7599	0.1080	99.45
Canada	7	0.714	0.0277	0.6593	0.7677	0.0726	99.24
Germany	7	0.554	0.0267	0.5020	0.6066	0.0694	99.55

Table 5 Relatedness support means by country

Country	*k*	Mean	S.E.	CI 95%		Tau	I^2 (%)
				Lower	Upper		
United States	15	0.688	0.0364	0.6162	0.7590	0.1403	99.79
China	9	0.741	0.0343	0.6741	0.8085	0.1024	99.65
Belgium	14	0.664	0.0245	0.6160	0.7121	0.0907	98.86
Spain	8	0.742	0.0316	0.6802	0.8040	0.0890	99.46
Canada	8	0.738	0.0210	0.6970	0.7794	0.0557	97.92
Israel	5	0.749	0.0643	0.6229	0.8751	0.1430	99.33

trend in 16 countries with the most data available, and found significant trends in four instances (Table 7). Most notably, autonomy support in China appears to have increased since the first data reported in 2007 through to 2022 ($b=0.0109$, $p=.009$, $R^2=9.62\%$, $k=57$). Likewise, results also indicate that autonomy support in South Korea ($b=0.0205$, $p=.007$, $R^2=29.81\%$, $k=16$), Turkey ($b=0.0200$, $p=.014$, $R^2=39.63\%$, $k=9$), and France ($b=0.0177$, $p=.016$, $R^2=39.76\%$, $k=9$) have also increased over time, however we must again caution that estimates from Turkey and France were based on relatively few datapoints. Interestingly, the data from Turkey were all published within a six-year period from 2015 to 2021, indicating that this change may have developed quickly and recently in that country.

Table 6 Autonomy thwarting means by country

Country	*k*	Mean	S.E.	CI 95%		Tau	I^2 (%)
				Lower	Upper		
United States	20	0.367	0.0337	0.3012	0.4331	0.1497	99.31
China	20	0.453	0.0205	0.4125	0.4928	0.0910	99.31
Belgium	21	0.266	0.0252	0.2166	0.3155	0.1148	99.48
Spain	29	0.245	0.0164	0.2132	0.2774	0.0877	99.3
Canada	10	0.268	0.0284	0.2121	0.3235	0.0891	98.84
Italy	12	0.285	0.0111	0.2637	0.3072	0.0365	91.88
Israel	8	0.289	0.0358	0.2186	0.3591	0.1003	98.43
South Korea	10	0.421	0.0375	0.3476	0.4947	0.1181	99.69
Estonia	8	0.309	0.0298	0.2501	0.3669	0.0832	98.37
France	6	0.452	0.0866	0.2823	0.6216	0.2095	99.32

Fig. 4 Mean estimates of autonomy thwarting by country

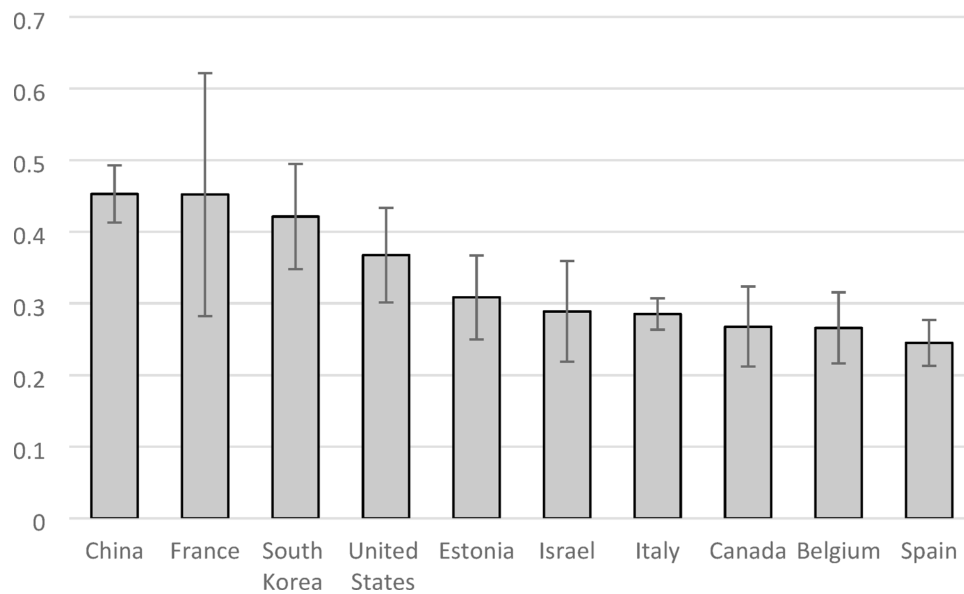

Fig. 5 Profiles of educational support and thwarting for the five most reported upon countries

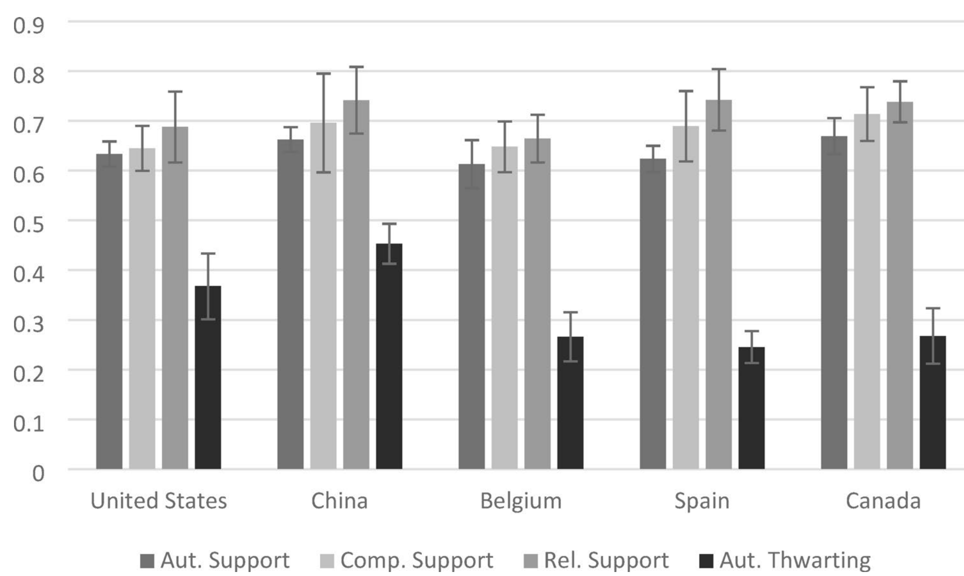

Table 7 Meta-regression with year of publication on mean autonomy support scores

Country	*k*	*b*	S.E.	*p*	95% CI		Tau	R^2 (%)	I^2 (%)	Year	
					Lower	Upper				First	Last
United States	99	0.0030	0.0024	0.218	−0.0018	0.0078	0.1264	0.52	99.74	2000	2021
China	57	0.0109	0.0042	0.009*	0.0027	0.0191	0.0911	9.62	99.41	2007	2022
Belgium	42	−0.0010	0.0054	0.852	−0.0115	0.0095	0.1612	0	99.72	2005	2021
Spain	41	0.0025	0.0048	0.600	−0.0070	0.0120	0.0854	0	99.21	2008	2022
Canada	37	0.0036	0.0046	0.429	−0.0054	0.0126	0.1120	0	99.71	2005	2021
United Kingdom	24	0.0001	0.0026	0.973	−0.0050	0.0052	0.0688	0	97.59	2003	2020
Italy	17	−0.0143	0.0127	0.261	−0.0393	0.0106	0.0874	1.99	98.28	2015	2021
Netherlands	11	0.0076	0.0149	0.609	−0.0216	0.0368	0.0981	0	99.45	2014	2021
Israel	16	0.0018	0.0076	0.810	−0.0131	0.0168	0.1189	0	99.2	2008	2021
South Korea	16	0.0205	0.0076	0.007*	0.0056	0.0354	0.0806	29.81	99.32	2011	2020
Germany	14	0.0065	0.0082	0.432	−0.0096	0.0226	0.1270	0	99.83	2007	2021
Greece	12	0.0038	0.0044	0.387	−0.0049	0.0125	0.0584	0	95.99	2005	2020
Estonia	9	0.0052	0.0053	0.326	−0.0051	0.0155	0.0540	0	97.22	2009	2021
Turkey	9	0.0200	0.0081	0.014*	0.0041	0.0359	0.0578	39.64	97.3	2015	2021
France	9	0.0177	0.0073	0.016*	0.0033	0.0321	0.0904	39.76	97.93	2006	2021
Norway	9	−0.0010	0.0123	0.936	−0.0250	0.0231	0.1488	0	99.62	2007	2020

"First' and "last" indicate the range of years for which data were available

Table 8 Meta-regression with year of publication on mean autonomy thwarting scores

Country	*k*	*b*	S.E.	*p*	95% CI		Tau	R^2 (%)	I^2 (%)	Year	
					Lower	Upper				First	Last
United States	20	−0.0048	0.0068	0.484	−0.0181	0.0086	0.1517	0	99.33	2004	2021
China	20	−0.0038	0.0056	0.503	−0.0148	0.0073	0.0924	0	99.33	2007	2022
Belgium	21	0.0061	0.0069	0.380	−0.0075	0.0197	0.1155	0	99.48	2007	2021
Spain	29	0.0174	0.0146	0.232	−0.0112	0.0460	0.0870	1.51	99.28	2018	2022
Canada	10	0.0011	0.0139	0.937	−0.0261	0.0283	0.0945	0	98.66	2013	2021
Italy	12	0.0093	0.0062	0.135	−0.0029	0.0214	0.0345	10.96	90.54	2015	2021
South Korea	10	0.0256	0.0329	0.438	−0.0390	0.0901	0.1208	0	99.7	2016	2020

"First' and "last" indicate the range of years for which data were available

Autonomy thwarting practices in education did not display any trend over time for the seven analyzed countries (Table 8). Despite relatively good sample sizes, these effects did not cover many years, thereby only speaking to change over a relatively small timeframe. This restricted range may be a reason we could not identify any trend over time. While analyses for competence support and relatedness support were conducted, they generally did not include enough studies to interpret with much confidence. Hence, these results are presented in the online supplementary materials and should be verified when more data are available (Tables S2 and S3).

In order to address RQs 4 and 5, we examined autonomy support at the national level with one estimate representing each of the 48 included countries. We began by adding the six cultural values measured by the Hofstede index. Only uncertainty avoidance was significant in explaining levels of autonomy support ($r=-.002$, $p=.006$, $R^2=12.63\%$, $n=48$ countries; Table 9). This indicates that countries that tend to avoid uncertainty are less likely to engage in autonomy supportive educational practices. However, this effect is small and explains little variance when compared that explained by other moderators. National values were not significant predictors of competence support or relatedness support (Table 9). When examining autonomy thwarting, a significant effect was once again noticed for uncertainty avoidance ($r=-.0024$, $p=.013$, $R^2=17.2\%$, $n=27$ countries). Somewhat unintuitively, it appears that countries higher in uncertainty avoidance reported lower levels of autonomy thwarting, in addition to the previously noted lower levels of autonomy support. Once again, this effect was very small.

The impact of GDP/capita (USD) of each country was then analyzed to see if wealthier and more developed countries tended to have higher (or lower) levels of support and thwarting. Results indicated no relationship between GDP and any of the three forms of support or reports of autonomy thwarting. The amount of government spending on education (operationalized as a proportion of GDP) was then assessed to see if government fiscal prioritization of education impacted the reports of students regarding perceived support or thwarting. No significant results were noted for autonomy, competence, or relatedness support

Table 9 National cultural values as moderators of National support and thwarting aggregates

Support variable	n	*b*	S.E.	*p*	CI 95%		Tau	R^2 (%)	I^2 (%)
Values					Lower	Upper			
Autonomy support									
Power distance	48	−0.0004	0.0008	0.647	−0.002	0.001	0.113	0	99.43
Individualism	48	−0.0001	0.0008	0.855	−0.002	0.001	0.113	0	99.34
Achievement orientation	48	0.0000	0.0008	0.988	−0.002	0.002	0.113	0	99.49
Uncertainty avoidance	48	−0.0020	0.0007	0.006*	−0.003	−0.001	0.105	12.63	99.36
Long term focus	48	−0.0003	0.0008	0.684	−0.002	0.001	0.113	0	99.45
Indulgence	48	0.0009	0.0009	0.285	−0.001	0.003	0.113	0.35	99.48
Competence support									
Power distance	23	−0.0011	0.0010	0.257	−0.003	0.001	0.092	1.29	99.18
Individualism	23	0.0002	0.0009	0.786	−0.001	0.002	0.095	0	99.11
Achievement orientation	23	0.0012	0.0011	0.310	−0.001	0.003	0.093	0.17	99.33
Uncertainty avoidance	23	−0.0008	0.0010	0.421	−0.003	0.001	0.094	0	99.32
Long term focus	23	0.0010	0.0013	0.442	−0.002	0.004	0.094	0	99.18
Indulgence	22	0.0007	0.0014	0.642	−0.002	0.003	0.094	0	99.27
Relatedness support									
Power distance	22	−0.0003	0.0010	0.778	−0.002	0.002	0.093	0	98.96
Individualism	22	0.0007	0.0009	0.448	−0.001	0.003	0.092	0	98.78
Achievement orientation	22	0.0002	0.0012	0.886	−0.002	0.003	0.093	0	99.22
Uncertainty avoidance	22	0.0014	0.0010	0.171	−0.001	0.003	0.088	6.02	98.97
Long term focus	22	0.0006	0.0014	0.681	−0.002	0.003	0.093	0	98.94
Indulgence	21	−0.0019	0.0012	0.094	−0.004	0.000	0.089	9.09	99.13
Autonomy thwarting									
Power distance	27	0.0011	0.0010	0.294	−0.001	0.003	0.101	0.68	99.05
Individualism	27	−0.0016	0.0009	0.063	−0.003	0.000	0.097	8.97	98.94
Achievement orientation	27	0.0005	0.0014	0.707	−0.002	0.003	0.104	0	99.07
Uncertainty avoidance	27	−0.0024	0.0010	0.013*	−0.004	−0.001	0.093	17.2	98.74
Long term focus	27	0	0.0010	0.965	−0.002	0.002	0.104	0	99.09
Indulgence	26	0	0.0011	0.983	−0.002	0.002	0.105	0	99.13

Table 10 Economic moderators of National need support and thwarting aggregates

Support variable	n	*b*	S.E.	*p*	CI 95%		Tau	R^2 (%)	I^2 (%)
Indicator					Lower	Upper			
Autonomy support									
GDP/capita (USD)	50	0.0060	0.0127	0.639	−0.0189	0.0309	0.1018	0	99.3
Government spending on Ed (% of GDP)	48	0.0036	0.0042	0.389	−0.0046	0.0118	0.0999	0	99.25
Competence support									
GDP/capita (USD)	23	0.0075	0.0079	0.346	−0.0081	0.0231	0.0557	0	97.56
Government spending on Ed (% of GDP)	23	−0.0020	0.0025	0.408	−0.0068	0.0028	0.0560	0	97.86
Relatedness support									
GDP/capita (USD)	20	−0.0114	0.0153	0.458	−0.0414	0.0187	0.0797	0	98.46
Government spending on Ed (% of GDP)	20	−0.0050	0.0054	0.363	−0.0156	0.0057	0.0785	0.27	98.4
Autonomy thwarting									
GDP/capita (USD)	27	−0.0190	0.0152	0.212	−0.0489	0.0109	0.0987	2.29	98.58
Government spending on Ed (% of GDP)	27	0.0112	0.0042	0.008*	0.003	0.0194	0.0897	19.38	98.31

(see Table 10). However, a significant result was found for autonomy thwarting ($b=0.0112$, $p=.008$, $R^2=19.38$, $n=27$). This indicates that students may report more experiences of autonomy thwarting in countries that spend more (as a proportion of GDP) on education. Importantly, the heterogeneity within country-level estimates remained substantial indicating the presence of additional moderators.

Discussion of results

By coding additional information into an already existing meta-analytic dataset, we demonstrate one way in which the field of SDT can maximize existing data to answer increasingly complex questions. Our primary results suggest that educational contexts have become more autonomy supportive over the past two decades. This trend is slight, but is promising given the consistent evidence on the benefits of autonomy supportive teaching (Guay, 2022; Howard et al., 2024; Okada, 2023; Reeve & Cheon, 2021). While several studies have compared samples from different countries and reported differing mean levels (e.g., Hagger et al., 2007, 2009; Soos et al., 2019), we expand this line of inquiry by providing estimates of national averages on need supportive and thwarting variables through meta-analytic integration. The differences between countries was not as stark as we had expected, but statistically significant differences were still noted. Some countries such as China demonstrated relatively high levels of both autonomy support and autonomy thwarting. This is interesting in light of discussion of Chinese education institutions (Yu et al., 2018), which may be prone to control and therefore autonomy thwarting, as evidence in our analyses. However, we also identified an important silver lining with Chinese students also reporting some of the higher levels of autonomy support. Students from other countries, such as Canada and Italy, reported high support for autonomy with less thwarting pressure.

While limited by potential sample sizes and range restrictions, the analysis of change within countries over time indicated that some countries are changing more rapidly than others. Students in Turkey in particular appear to have experienced more autonomy supportive educational environments in a very brief period of time (approximately 6 years), while China, South Korea, and France also noted increased autonomy support over somewhat longer periods of time (9–15 years). While education in China may face challenges (Yu et al., 2018), it appears government interventions in that country may be yielding some success. While it is encouraging that no countries displayed reductions in autonomy support or increases in autonomy thwarting, it appears more work can be done to translate the benefits of need-supportive teaching into classrooms.

The national-level analyses indicate that while some cultural and economic factors may impact the perspectives of students, the vast majority of variance was not explained by these national indicators. This result indicates that students can have autonomy supportive educational experiences regardless of how wealthy a country is, or even how fiscally prioritized the educational system is by the government. Instead, these largely null findings suggest that more proximal factors are likely to impact how need supportive or thwarting the student experience is likely to be (Vallerand, 1997). Much of this, we suspect, will be classroom-level factors relating to teachers, but it may also be attributable to more specific government education policy, or school-level administrative choices (Ryan & Weinstein, 2009; Ryan, 2024; Yu et al., 2018). The field of SDT has done an excellent job of describing individual and dyadic factors that impact student perceptions of support and thriving (Reeve & Cheon, 2021; Su & Reeve, 2011; see Howard et al., 2024 for a review), but future research may need to focus on hierarchical factors to better explain the environment teachers and students are expected to function within (Ryan, 2024; Yu et al., 2018). We would also encourage future research to adopt similar methodologies to test the proposition of universality that is central to SDT. Specifically, evidence towards this could be seen in the relationships between SDT variables and covariates across different countries or moderated by variables such as national values (e.g. Slemp et al., 2024), as well as any trend in these correlations over time.

It is reassuring to know that as more data is collected and added to the database, these analyses will become increasingly precise in discerning trends over time, and analyzed in conjunction with other national level factors in a more comprehensive manner. Given the noted influx of data in recent years (see Fig. 1), analyses such as this would have been difficult just a few years ago. A few years from now, we expect much more nuanced research to be achievable, and we hope results such as this can help influence policy decisions.

Conclusion

The acceleration of psychological science is making it increasingly impossible to keep up with published research. This is an inherent limitation of the text-based journal article system that academic science has relied upon for the past 400 years. Recently we have seen the move from hardcopy to predominantly digital dissemination of published works, allowing researchers easier access to research, to the benefit of all involved. However, we need to develop more scalable ways of managing research data and findings to supplement this text-based system. This article provides one such method by introducing the living meta-analysis of Self-Determination Theory. This database currently includes data from a range of existing SDT meta-analyses, and will be expanded in time to (hopefully) include the entirety of research involving SDT variables in a perpetually updating manner. The empirical example provided here demonstrate how large-scale analyses that may otherwise take years to complete can be conducted in a comprehensive manner far more efficiently. Importantly, the new data we coded (means, SDs, and ranges) are now part of the living meta-analytic database, which is publicly available, and therefore these studies will never need to be coded again by future meta-analysts.

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Declarations

Conflict of Interest Authors declare that he/she has no conflict of interest.

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