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REVIEW ARTICLE

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Organizational and psychological measures for data center energy efficiency: barriers and mitigation strategies

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Abstract It was last estimated that in 2020, data centers comprised approximately 2% of total US electricity consumption, with an estimated annual growth rate of 4%. As our country increasingly relies on information technology (IT), our data centers (DCs) will need to increase their energy efficiency (EE) to stabilize their energy consumption. The task of studying EE in DCs is complicated by the interconnected nature of humans and mission-critical technical systems. Moreover, the literature tends to focus on technology solutions such as improvements to IT equipment, cooling infrastructure, and software, without addressing organizational and psychological drivers. Our research demystifies the complex interactions between humans and DCs, by asking What non-technical barriers impede EE investment decision-making and/or implementing energy management strategies? To begin to answer this question, we perform a literature review of 86 resources, ranging from peer-reviewed journal publications to handbooks. We also consider related fields such as organizational behavioral management and energy intensive buildings. We develop a public Zotero library, perform content coding, and complete a rudimentary network analysis. Our findings from the literature review suggest that (1) technological solutions are abundant in the literature but fall short of providing practical guidance on the pitfalls of implementation, (2) making energy efficiency a priority at the executive level of organizations will be largely ineffective if the IT and facilities staff are not directly incentivized to increase EE, and (3) there is minimal current understanding of how the individual psychologies of IT and facilities staff affect EE implementation in DCs. In the next phase of our research, we plan to interview data center operators/experts to ground-truth our literature findings and collaboratively design decarbonization policy solutions that target organizational structure, empower individual staff, and foster a supportive external market.

Keywords Data centers · Organizational behavior · Network analysis · Public policy

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s12053-022-10078-1.

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Introduction

It was estimated that in 2020, data centers comprised approximately 2% of total US electricity consumption, with an annual consumption growth rate of 4% (Shehabi et al., 2016, 2018). While a shift to cloud computing has allowed for service growth to outpace energy consumption growth, in 2021, data centers consumed between 1.1 and 1.4% of electricity

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globally (Kamiya, 2022). As the global economy increasingly relies on information technology (IT), our data centers will need to continue to adopt energy efficiency (EE) strategies to stabilize their energy consumption (Shehabi et al., 2018). See Vasques et al. (2019) for a review of EE and demand response opportunities for data centers. Although cost-effective EE strategies are heralded in academic and practitioner-facing resources, experts remain concerned about near-term energy demand growth and sluggish mitigation efforts (Masanet et al., 2020). While many EE measures are technically feasible and cost-effective, factors such as uncertainty, risk aversion, lack of information, technical aptitude, split incentives, and other human and economic factors may help explain why EE actions are generally not undertaken in data centers (Klemick et al., 2019; Coyne & Denny, 2021; Koomey & Tylor, 2017).

The study of technology adoption and energy management strategies in high-tech buildings such as data centers is complicated by the interconnected nature of humans and technical systems. Energy efficiency improvements in data centers require not only the availability of more efficient equipment and technologies, but also awareness of opportunity and incentive to implement change among key stakeholders. The disaggregation of responsibility and decision-making authority among stakeholders, coupled with the mission-critical nature of data centers, results in a set of EE barriers distinct from other commercial buildings.

We investigate these phenomena to better understand the decision environment around EE in data centers. More specifically, we perform a literature review to systematically identify (1) existing barriers and solutions to promoting EE adoption in data centers and (2) areas where barriers are not yet well understood.

Methodology

This analysis is the first step in a two-phased research program. Phase I, presented here, constitutes a literature review of barriers and mitigation strategies to increasing EE in data centers. The goals of this literature review are twofold: (1) to systematically identify barriers that can be addressed with existing tools and supporting materials in the field, and (2) to systematically identify gaps in the literature where barriers are not well understood, to be explored in follow-on research. Phase I reflects an extensive search of academic journals, practitioner guides, news articles, and online databases; material coding; and a synthesis of the findings, potential gaps, and next steps.

This review focuses on data center-specific literature, but also includes findings in related fields, such as energy intensive buildings (e.g., laboratories, hospitals) and commercial buildings. The review also focuses on non-hardware solutions (including behavioral decision-making and IT efficiency improvements) and often overlooked small[1] data centers, which have a unique set of barriers and mitigation strategies. First, we conducted a search of Google Scholar, Science Direct, Web of Science, and National Laboratory archives using key search phrases such as "data centers + energy efficiency + barriers" and "sustainable data centers 'energy management.'" See Appendix 1 for a full list of search strings. The search took place between November 2020 and March 2021.

A subset (40) of relevant readings was identified from all the resources found in the initial search. Next, we identified references in each of the original papers to investigate for a second round of paper selection, from which we identified an additional 46 readings to be relevant. The complete inventory of the 86 reviewed resources can be found in Supplementary information.

Table 1 illustrates the counts of resource types referenced in this work (please see Appendix Table 3 for a list of resource type definitions). We saved our findings in Zotero[2] and created a shared library[3] for further organization and coding.

After the relevant papers were identified for review, the papers were randomly assigned to be read by each of the three researchers. Over the course of 3 months, we met weekly to discuss our readings, annotate the barriers and other key findings identified in the paper, and develop a framework for synthesizing our findings. We employed a

[1] Defined as those under 5000 ft.^{2}.

[2] Zotero is a bibliography software that helps researchers organize resources by collections, tags, and keywords: https://www.zotero.org/.

[3] The Zotero library used in this research is publicly available at the following URL: https://www.zotero.org/groups/4538694/organizational_and_psychological_measures_for_data_center_energy_efficiency_references.

Table 1 Summary quantity of each resource type. Please see Appendix Table 3 for a list of resource type definitions

Resource type	Data centers	Related fields	Sub-total
Energy and Computing Journals	16	11	27
Whitepapers	11	1	12
IEEE Publications	10	0	10
National Laboratory Reports	4	3	7
Other Science Journals	3	4	7
Conference Proceedings	6	0	6
Design or Operations Guidance	6	0	6
Miscellaneous	1	4	5
Web Content	4	0	4
Newspapers or Magazines	2	0	2
Sub-total	63	23	86

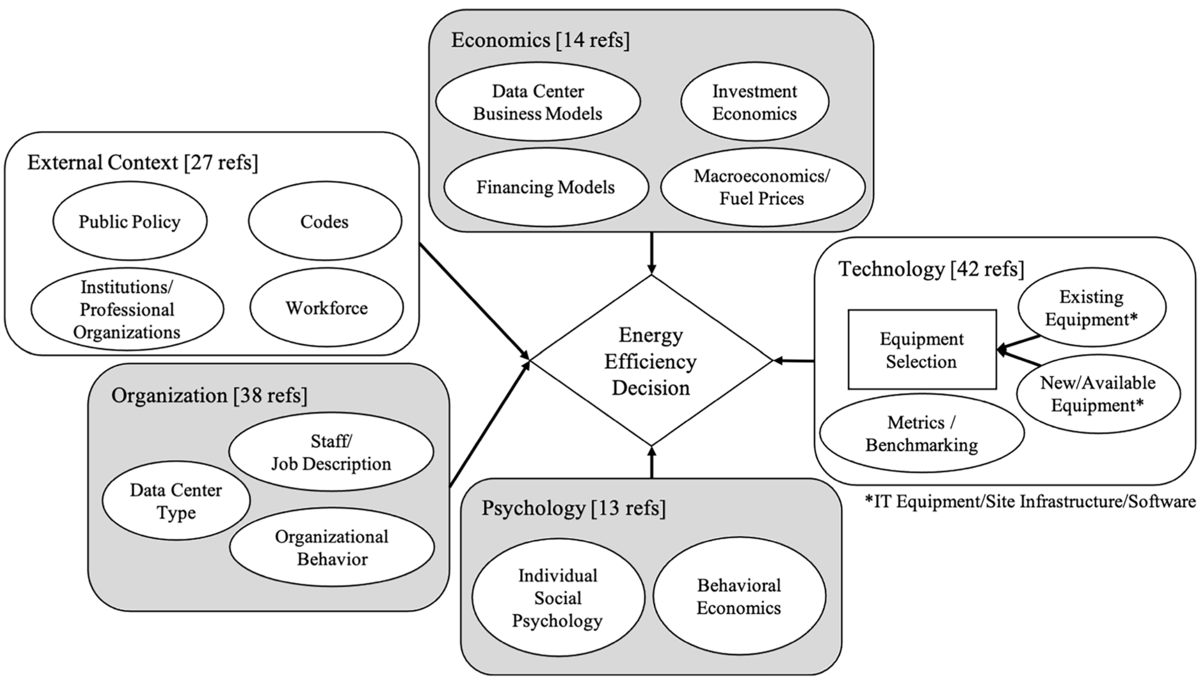

Fig. 1 Coding taxonomy. The five main components of an EE investment decision profile adapted from Hanus et al. (2018) for data center owners and operators: (1) economics, (2) technology, (3) psychology, (4) organization, and (5) external context

taxonomy to frame both the scope of our research and an organizational system by which barriers would be systematically studied. This taxonomy, adapted from Hanus et al. (2018), explores the external and internal factors that may directly or indirectly influence the decision to invest in data center energy efficiency. As shown in Fig. 1, we organized influential factors into five main categories.

Once this taxonomy was adapted for the data center EE literature, each researcher reviewed each paper in the library and independently tagged them according to the five main components in the organizational system described in Fig. 1. We were free to assign multiple tags to each paper, when necessary, though attempted to be judicious in the coding to avoid dilution of results from the exercise. For instance, a researcher might determine that a given paper discussed matters related to economics as well as technology and assign that paper both tags. Alternatively, a researcher might determine that a paper focused solely on technology. After independently coding all of the papers, we reconvened to compare our coding for each paper. We discussed our reasoning and explained our understanding of each tag definition. After this meeting, we went back through the papers once more to revise our tags. Finally, we met for a final time to compare our individual tags and determine a final group tag for each paper. Ultimately, the coding approach involved individual and collective reflection and communication, the generation of conceptual definitions, and data reduction using the organizational system outlined in Fig. 1 (Deterding & Waters, 2021). The final library of resources, the taxonomic codes assigned by each researcher, and their final consensus taxonomic coding can be found in the Supplementary information.

To understand the prevalence of these decision-making components in the literature, we calculated (1) total occurrences of each unique tag and (2) frequency of tag combinations. As an example, we looked at the number of times we tagged *Economics* in our papers as well as the number of times we tagged *Economics* & *Technology*, *Economics* & *Psychology*, *Economics* & *Organization*, *Economics* & *External Context*, *Economics* & *Technology* & *Psychology*, etc. The following section details our findings from this methodology.

Results

Organizing entries in the library by theme allowed for analysis of the current state of the literature as well as identification of potential disciplinary silos. The thematic tags we assigned to each paper were modified from the schema employed by Hanus et al. (2018). As shown in Fig. 1, the final taxonomy included five components to EE decision-making: economics, technology, psychology, organization, and external context. For the purposes of this research, we defined these categories as follows:

- *Economics* refers to the effects of underlying macroeconomic conditions and firm-level financial health, as well as data center business models.
- *External context* refers to the policy environment in which firms operate, specifically the external regulatory and normative factors which influence decision-makers. For example, interest rates and the accompanying availability of credit are external context which influences decision-makers.
- *Technology* refers to hardware, software, built environment, benchmarking, and metrics that comprise the technological frontier of the data center industry.
- *Psychology* refers to the individual psychological factors that influence human behavior, including individual biases and heuristics.
- *Organization* refers to the influence the structure, culture, and characteristics of an organization have on the conditions and behavior of the underlying data center.

Categories

As described in the "Methodology" section, researchers reviewed each paper in the library, independently assigned tags according to this categorical taxonomy, and then reconvened to adjudicate entries where there was disagreement. After all tag disagreements were reconciled, the final library of papers with thematic tags was analyzed. The library with original tag assignments by each researcher alongside the final thematic coding can be found in the Supplementary information. As shown in Fig. 2, the *Technology* tag was most prevalent in this literature review, whereas the *Psychology* and *Economics* tags were used less often.

Library entries with appropriate breadth of focus were assigned multiple tags. Table 2 lists each unique tag combination to be assigned at least one library entry, as well as citations for each of those entries. The unique tag combination assigned to the most papers (24) was the single tag coding of *Technology*, indicating that a pure focus on technology was the most frequent research topic. The most common tag pairings (tag combinations comprised of exactly two categories) assigned to the papers were *Psychology & Organization* and *Technology & Organization*, representing 11 papers each. Figure 3 is a plot of the count of the quantity of papers to receive each number of thematic tags. Fewer than 10% of entries in the library (eight) were sufficiently broad in scope to receive three or more tags.

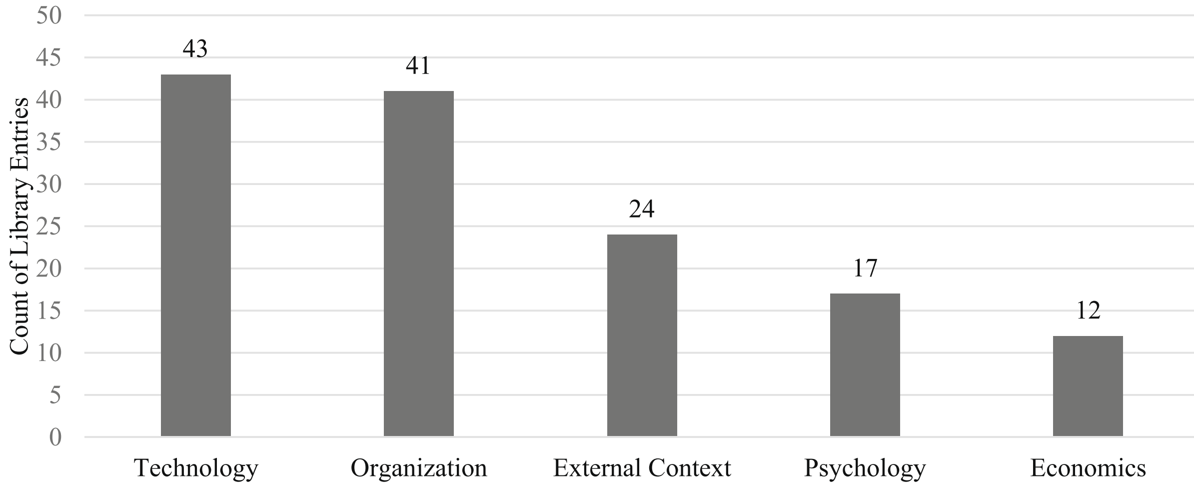

Fig. 2 Total tag count. This bar chart represents the count of library entries which received each tag. Note that entries could be assigned multiple tags so the sum of these tag totals is not equal to the total number of library entries. *Technology* and *Organization* are the most frequently addressed topics within the library

Clustering analysis

As shown in Fig. 3, the majority (44) of papers received exactly one tag, with the overwhelming majority of the remaining papers (34) receiving exactly two. The 34 papers that were assigned exactly two tags presented an opportunity for clustering analysis. The clustering analysis enables us to visually identify central nodes, key overlaps, and potential gaps in the existing literature. In contrast to the robust quantity of papers with exactly two tags, only seven papers received three tags, one received four, and zero papers received all five tags.

In addition to there being a small quantity of them, three-, four-, and five-tag papers also potentially confound cluster analysis. Given our five thematic categories, all papers that receive three or more tags contain at least 60% of the categories, making them more informative on which topics they exclude rather than those they include. This is a valid line of analysis but is counter to the insight provided by analyzing tag pairings, which express relationships between included nodes. Considering this confounding factor, as well as the small overall quantity of these papers, the network analysis includes only papers tagged with exactly two themes.

Figure 4 is a diagram showing the results of the clustering analysis of the library entries that received exactly two tags. Nodes represent the five thematic categories, and the connections between nodes correspond to the quantity of papers which received that combination of tags. Gaps in the diagram reflect tag pairings which did not occur in our data set.

Discussion

After assigning tags, we then analyzed their relative frequency for insights. We combined this tag analysis with our review of the literature. We mapped our clustering analysis onto the synthesized literature findings, and discussed among researchers until we reached consensus on the thematic takeaways of our results which we will now discuss, beginning with the centrality of the *Organization* thematic tag. If a reviewed paper has at least two thematic tags, 80% of the time it is an *Organization* tag. Additionally, *Organization* is the only thematic category to overlap with *Psychology*. This indicates that within our library, papers covering organizational topics are more likely to be interdisciplinary and less likely to be siloed. Another key finding is that *Technology* is the most frequently tagged component of decision-making in our literature review. Additionally, it is often siloed from other categories. From the papers covered in this scope of work, the *Technology* papers often do not provide much detail regarding the implementation of the technologies and rarely discuss

Table 2 All 20 unique tag combinations (rows) were assigned to at least one library entry. This table includes the count of those items and references. Papers with the sole focus of *Technology* more than double any other unique tag combination. All 86 library entries are represented in this table

Tag combinations	Count of library entries	References
Technology	24	Yuventi & Mehdizadeh, 2013; Pawlish & Varde, 2010; Luo et al., 2019; Hamann, 2008; Li et al., 2020; Data Center Dynamics, 2020; Delforge & Whitney, 2014; Song et al., 2015; Mahdavi & Greenberg, 2017; Kliazovich et al., 2013; Schuetz et al., 2013; Beloglazov & Buyya, 2010; Yevgeniy Sverdlik, 2018; Sartor & Greenberg, 2018; Jones, 2018; Ogura et al., 2018; Wierman et al., 2009; Sartor, 2018; Judge et al., 2008; Chen et al., 2016; Shuja et al., 2016a, b; Pore et al., 2015; Shehabi et al., 2016; Derrick & Joy, 2014
Psychology, Organization	11	Aarons et al., 2011; Molla et al., 2009; Maiorano, 2018; Heller et al., 2010; Buyya et al., 2010; Wang et al., 2013; Chainer et al., 2017; Bossink, 2020; Cresswell & Sheikh, 2013; Seifert, 2018; Hanus et al., 2018
Technology, Organization	11	Greenberg et al., 2006; Dayarathna et al., 2016; Shehabi et al., 2018; Paul et al., 2017; König, 2020; Andrews & Johnson, 2016; Johnston & Berger, 2011; Klemick et al., 2019; Kristina Stokes, 2017; Greenberg & Herrlin, 2017; Guitart, 2017
External Context	9	Cook et al., 2014, 2017; Adjei et al., 2021; Solomons & Spross, 2011; Shamshoian et al., 2005; Brown et al., 2007; Delaney & Smith, 2006; Mission Critical Facilities, Technology Spaces, and Electronic Equipment Technical Committee 2011; York et al., 2017
Organization	8	Lansing, 2020; Mills et al., 2008; Singer & Tschudi, 2009; Lin et al., 2012; Coro Foundation n.d.; Romero et al., 2020; Morgenstern et al., 2016; Delforge, 2014
Technology, External Context	4	Beaty, 2005; "Data Center Thermal Runaway" 2007; Gao et al., 2012; Masanet et al., 2020
External Context, Organization	3	Howard & Holmes, 2012; Kaplowitz et al., 2012; Loper & Parr, 2007
Psychology	2	Chapman et al., 2020; Lutzenhiser, 1993
External Context, Economics	2	Qureshi et al., 2009; LearnIT, n.d.
Organization, Economics	2	Heydari et al., 2011; Brill, 2007
Economics	1	"Colocation Pricing Guide" 2019
Technology, Economics	1	Shuja et al., 2016a, b
External Context, Organization, Economics	1	Lawrence Berkeley National Lab, 2020
External Context, Psychology, Economics	1	Tidd & Bessant, 2020
External Context, Psychology, Organization	1	Shehabi et al., 2008
Psychology, Organization, Economics	1	Daphne Leprince-Ringuet, 2021
Technology, External Context, Economics	1	Wierman et al., 2014
Technology, External Context, Organization	1	Whitney & Kennedy, 2012
Technology, Organization, Economics	1	Bennett & Delforge, 2012
External Context, Organization, Psychology, Economics	1	Palm & Thollander, 2010

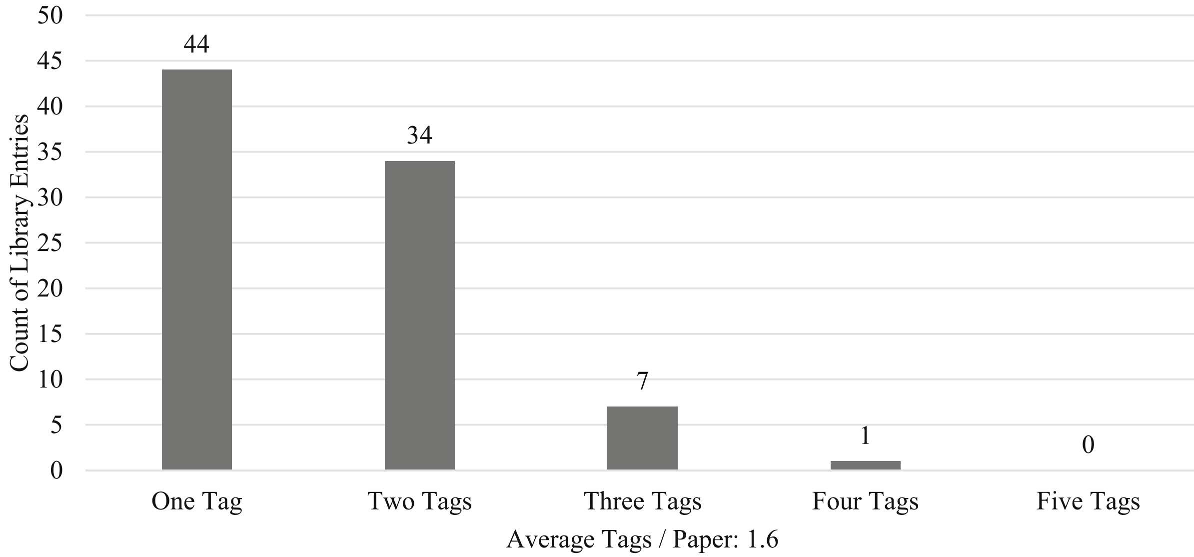

Fig. 3 Tag quantity count. The number of papers assigned each quantity of tags. On average, papers received 1.6 tags. The majority of papers received a single tag, and no paper received all five potential tags

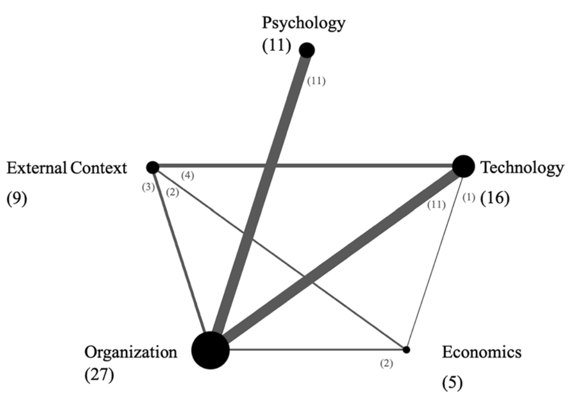

Fig. 4 Tag Pairings Clustering Diagram. This figure is a network diagram plotting the tag pairings in our papers that received exactly two tags. The thickness of the connections scale with the number of papers that contained the corresponding tag pair. The numbers beneath each connection line in parentheses are the count of papers that make up the connection. Each node in the diagram corresponds to one of the five paper tags, with their total representation within the dual tag papers listed in parentheses. The size of the nodes corresponds with the number of tag pairs that include the node. Length of line does not correspond to any property. Note the isolation of *Psychology* as a category, which only connects to a single other node (*Organization*)

common pitfalls in their adoption. Rather, the focus of *Technology* papers often centers on the design, performance, and technical minutiae of the technology in question. Although case studies may explain the technology implemented at a given site, they often exhibit a lack of discussion around lessons learned or organizational/psychological aspects of the investment decision.

Separate from the *Technology* tagged papers is a substantive number of *Organization & Psychology* tagged papers, indicating that the EE literature does recognize organizational behavior theory as a valid line of inquiry for mitigating barriers to implementation. However, in reading these papers, there seems to be a lack of acknowledgement of the disconnect that can exist between policies implemented at the executive level of an organization and the actual practices of the IT and facilities staff (Lansing, 2020). For instance, if an organization decides to install smart meters in all of their data centers, they may go underutilized by a staff that does not know how to operate them and leverage their energy saving capabilities. This issue can be particularly pervasive in small data centers, which may not have the capital or other resources, training, or economies of scale to properly implement these measures (Shehabi et al., 2018). Despite being relevant for small data centers, many commercial EE products are marketed towards larger data centers, which can be easier and more profitable to serve (Bennett & Delforge, 2012).

Furthermore, corporation-wide EE policies may be deprioritized by IT and facilities staff who are aiming to maintain reliability metrics, often their primary measure of job performance. If nominal statements of the strategic value of EE by executives are not paired with accompanying adjustments to how performance is measured, employee behavior will not change (Howard & Holmes, 2012). Yardsticks against which employee performance is measured will inevitably factor into what decisions that employee makes, and what they prioritize. One study found that C-suite executives were more likely to cite EE as the second most important of five possible upgrades, while engineers ranked it as the least important of the five options (Lansing, 2020). Ultimately, it is not enough to make EE a strategic priority at the C-suite level; there should also be links in place between the corporate goals and IT/facilities staff behavior such as energy management plans, training materials (internal or external), and updated performance metrics (Heydari et al., 2011). Re-examining the alignment of performance incentives and ensuring that day-to-day operators are equipped with necessary knowledge and training are key to successfully executing organizational-level policies.

Moreover, our literature review underscored an area ripe for future research: the role of individual psychology in data center investments and operation. For instance, Hanus et al. (2018) revealed that an individual's trust in various information sources inspires or inhibits EE technology adoption in commercial buildings. They also found that EE decision-makers may be prone to fear of change, irrationality via mental accounting, and risk aversion (Hall et al., 2013; Thaler, 1985). The IT and facilities staff in charge of implementing EE measures in data centers may have political ideologies and values that misalign with internal and external influences. For example, a lack of recognition within an organization for energy efficiency means that there is little motivation for staff to prioritize it, especially if those staff members are personally skeptical of the value of reduced energy consumption. Ultimately, the individual psychology of the EE decision-makers may interfere with any policies or goals set by the organization. While these ideational and psychological effects, as well as their limitations, are investigated in the related fields literature (Kaplowitz et al., 2012; Morgenstern et al., 2016), they remain understudied with respect to data centers.

Different barriers to EE in data centers must necessarily be addressed in different ways (Appendix Table 4). These interventions are not all equally costly or challenging. It is useful here to introduce the concept of organizational inertia first introduced by Hannan and Freeman in 1977, and then expanded upon in Hannan and Freeman (1984). Organizations are inertial: They will not change spontaneously, owing to nonzero transaction costs. If constituent members of an organization perceive organizational inertia, we can then scale their perceived cost of adopting a change. In future work, we intend to evaluate this model through interviews and surveys of practitioners. The model predicts that interventions that must overcome higher levels of organizational inertia are adopted less frequently than those interventions required for overcoming lower levels of organizational inertia. We intend to evaluate this model in phase II of our research.

Conclusion and recommendations

This literature review uncovers a few themes that merit further investigation in a phase II interview study. However, phase I yields the following eight findings and initial recommendations for overcoming associated challenges:

1: *Establish an EE champion*: Overcoming organizational inertia and successfully implementing an EE project can be time consuming, particularly if an organization has not previously implemented such improvements. As such, projects may be successful if a responsible project "champion" is assigned (Seifert, 2018). Establishing an EE champion to lead these efforts (rather than leaving it up to individuals as they have free time) is most effective when written formally into a job description. These champions should possess a wide variety of skills, including familiarity with the company and its business processes, as well as technical software expertise.

2: *Make EE a strategic priority*: Compared to uptime and reliability, energy performance takes a back seat in terms of organizational priority in data centers. Stakeholders in an organization inevitably have their foremost priorities and concerns, incentivized by their job descriptions and performance expectations. For most stakeholders aside from a facility manager (whose department typically foots the data center energy bill), energy management is likely a low priority, and potentially an opaque aspect of operations. An important step in any change is to first assess the stakeholders involved and their likely motivations. Increasing the visibility of this issue among all stakeholders, but particularly the C-suite, is critical in order to achieve buy-in for improvement projects. Furthermore, it is important to establish a culture of continuous improvement—as project success is correlated with the degree to which change management is institutionalized within the IT organization's policies and culture (Solomons & Spross, 2011). One way to accomplish this is implementing a structured energy management system via strategic energy management (SEM) programs, such as 50001 Ready, or ISO 50001 certification.

3: *Dissolve internal silos*: Organizational silos, particularly between IT, facilities, and management, can undermine EE efforts. These silos are common in the industry as "communication between facilities staff that operate and maintain the data center facility and the staff who specify, operate, and maintain the IT equipment housed in the data center is often lacking" (Howard & Holmes, 2012). Creating a cross-disciplinary continuous improvement plan can help improve communications between different business units, and can create an official forum for collaboration. This improvement team can enable a more holistic energy management approach, and can create internal processes and incentive structures that are coordinated and aligned with EE goals. These efforts can help coordinate capital expenditure decisions, establish common reporting practices, and set goals. It is important to review how an organization allocates resources and hardware, as well as how billing and accounting function for these projects, as these practices often drive or explain the interests of stakeholders.

4: *Increase awareness of EE opportunities*: Awareness of data center EE opportunities and their benefits varies among data center owners and operators. Continued promotion of EE products, technologies, and services is important for continued proliferation. Additionally, resources (both technical and organizational) that instruct and assist organizations in how to go about implementing technology solutions must be developed and promoted to the right audiences. For instance, the Lawrence Berkeley National Laboratory Center of Expertise (CoE) for Energy Efficiency in Data Centers website boasts a multitude of training materials, and even provides resources aimed at small data centers (Greenberg & Herrlin, 2017). These types of awareness campaigns and training programs are particularly important to ensure data center personnel and stakeholders are operating their facilities with knowledge of efficiency improvement opportunities. These direct interventions are best paired with formal benchmarking groups, which can identify industry leaders and allow others to adopt their best practices. The *European Code of Conduct on Data Centre Energy Efficiency* represents one such benchmarking effort (Acton et al., 2021; Avgerinou et al., 2017).

5: *Realign split incentives*: Organizational leadership should examine where split incentives exist within their organization with respect to data center EE. The most common of these as described in the literature is the IT-Facilities divide, where IT sets capacity demands and facilities foot the energy bill. This separates the stakeholders who benefit from efficiency investments from those who finance efficiency investments. Consolidating facilities and IT hardware groups under one manager or centralizing capital expenditure decisions can help overcome this split incentive, as can factoring energy performance into contracts for in-house IT staff. Colocation facilities face especially significant split incentives, as the facility operator and IT operator are entirely separate organizations. The most extreme example of this divide occurs in *cost-plus* facilities, which document and pass through all operating costs of the data center to the customer with an automatic markup (Delforge & Whitney, 2014). In these pricing schemes, facility operators are not merely insulated from the financial benefits of energy efficiency; they are actively financially punished. Any reduction in energy cost carries a proportionate reduction in markup revenue. Sub-metering and pricing transparency represent the first steps towards aligning these incentives.

6: *Invest in workforce development*: The availability of skilled and qualified staff is a problem in the data center industry at large, particularly with regard to EE. There are multiple programs by which data center operators can attain education and certification of data center energy management knowledge (e.g., Data Center Energy Practitioner Training[4]). Continuing to invest in those programs can help improve EE in data centers and also provide professional credentials that have value in job market (Guitart, 2017).

7: *Overcome technical risk aversion:* It is important that stakeholders at all levels of the organization (though particularly in IT) are aware of how EE actions can not only save energy, and ultimately operating costs, but also can bolster reliability and resiliency, by extending the life of equipment and reducing the likelihood of outages and downtime, for example. Risk aversion is pervasive among organizational leadership, and particularly IT and facilities managers (Klemick et al., 2019). Aside from spreading awareness of the multiple benefits of EE, increasing confidence in the performance of products through demonstration projects and case studies is an important element to advancing energy efficiency. Organizations can also initially prioritize low-risk measures as they begin their EE journey.

8: *Mitigate barriers to initial capital investment*: Internal siloing of capital and operational expenditures can lead to a disconnect in understanding that sometimes high capital cost investments yield extremely high operational savings, resulting in a relatively high return on investment (ROI) or short simple payback (SP) period. It is important that if these two decision responsibilities (capital and operational) are siloed, that staff at least communicate in simple terms the benefits of these investments using common metrics like ROI or SP. Additionally, government procurement programs can play a role in helping reduce costs of new-to-market products and ultimately reduce costs of manufacturing through economies of scale. Organizations should also leverage financial assistance to accomplish EE improvements (e.g., utility or state incentive programs). Though these programs have become more widespread in recent years, marketing/awareness of these programs could be improved. Programs should offer both prescriptive and custom pathways in an effort to attract efficiency projects of different complexities and scales. Lastly, alternative financing mechanisms—such as energy savings performance contracts (ESPCs)—can alleviate initial investment costs while providing measurable data on project performance (Loper & Parr, 2007).

To further refine the recommendations and policy implications surrounding organizational and psychological barriers to EE in data centers, future work should examine how these barriers impact decision-making in a variety of data center contexts. For instance, what are the unique organizational and psychological barriers and solutions for data centers of varying size and function? Vasques et al. (2019) suggest that small and medium data center operators are often overlooked in EE and demand response policy and incentive design—what other subcategories might be neglected? We propose an interview study to develop empirical data to address more nuanced questions that our literature review could answer.

This could entail interviewing data center owners and operators, vendors, academics, and other data center EE experts to (1) ascertain the prevalence of barriers identified in the literature review across data center decision-makers, (2) identify and characterize new barriers not yet addressed in the literature, and (3) prescribe effective policies for addressing these barriers. The interview protocols will be based on our

[4] Data Center Energy Practitioner (DCEP) Training is available at https://datacenters.lbl.gov/dcep.

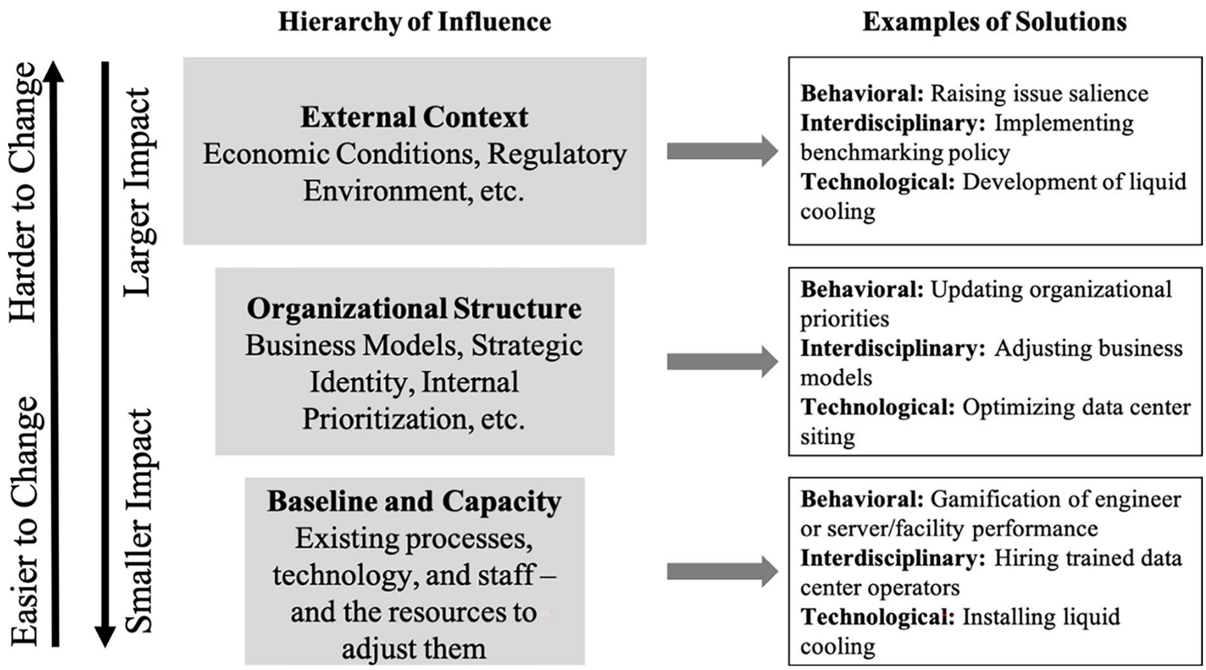

Fig. 5 Influence hierarchy. This graphic represents the hypothesized hierarchy of influences in EE decision-making in data centers that we surmised from this literature review and plan to test in the phase II interview study. The environment of barriers to EE in data centers goes from broadest effect (e.g., system-wide factors) to narrowest (e.g., individual racks and centers). Inertia to change refers to how much effort is required to institute solutions in each of these categories; inertia increases moving from the narrowest effects up to the broadest effects

theory of a hierarchy of influences in EE decision-making in data centers, which is based on our findings from the literature (Fig. 5).

We hope to use the interview protocol to test our theory of hierarchal decision-making and answer research questions such as these:

i. What are the differences in organizational and psychological barriers to EE between small data centers and medium/large data centers?
ii. How do experts and owners/managers differ in their perspectives to EE barriers?
iii. What additional resources can be provided to overcome organizational and psychological barriers?
iv. What are the differences in performance metrics across data center types?
v. How do procurement processes differ across data center types?

Ultimately, our aim for phase II is to confirm and expand on our preliminary findings from phase I, which are that (1) technological solutions are abundant in the literature but fall short of providing practical guidance on the pitfalls of implementation, (2) making energy efficiency a priority at the executive level of organizations will be largely ineffective if the IT and facilities staff are not directly incentivized to increase EE, and (3) there is little focus on and current understanding of the impact of the individual psychologies of IT and facilities staff on EE implementation in data centers.

Appendix 1

Search strings

1. Data centers + energy efficiency + barriers
2. Sustainable data centers “energy management”
3. Barriers sustainable data centers
4. Small data centers barriers to energy efficiency
5. Diffusion of adoption of management of energy in data centers
6. Data center decision-making energy
7. Energy efficiency data center
8. Data center operations
9. Energy efficiency decision-making industrial
10. Data center energy efficiency

Table 3 Definitions of resource types

Resource type	Definition
Energy and Computing Journals	Academic publications that focus on either energy or computers and related disciplines
Whitepapers	Research, surveys, or policy guidance from all institutions aside from academic journals
IEEE Publications	Materials published by IEEE in-house journals. Includes conference proceedings from IEEE conferences
National Laboratory Reports	Research conducted at and formally published by a US government national lab such as Argonne or Berkeley National Lab
Other Science Journals	Academic publications in fields besides energy or computing
Conference Proceedings	Conference presentations or publications of conference submissions
Design or Operations Guidance	Guidance on the design or operation of data centers
Miscellaneous	Books, training materials, and other miscellanea
Web Content	Websites or blog posts relating to data centers
Newspapers or Magazines	Journalistic outlets or trade publications

Table 4 Barriers, interventions, and goals

Barrier	Interventions	Goals
Low EE Salience in IT Staff	• Institutionalize the change within the C-suite (Schuetz et al., 2013) • Certification and professional recognition (York et al., 2017) • Reference best practices guides (York et al., 2017) • Labeling (York et al., 2017)	• Lasting change and project success are correlated with the degree to which change management is institutionalized within the IT organization's policies and culture • Increase awareness of and expertise in working with energy-efficient products, technologies, and services • Create customer awareness of differences in EE among targeted products
Technical Risk Aversion	• Demonstration products and customer testimonials (York et al., 2017) • Educate other stakeholders as to how EE actions can actually bolster reliability and resiliency, and reduce O&M costs (Lawrence Berkeley National Lab, 2020) • Initially prioritize low-risk measures (Lawrence Berkeley National Lab, 2020)	• Increase confidence in performance of products • Demonstrate a multitude of benefits from the EE measure • Demonstrate a proven process for implementing measures
Lack of Knowledge, Bounded Rationality	• Mass advertising (York et al., 2017) • Training (York et al., 2017)	• Increase awareness of products • Increase awareness of and expertise in working with energy-efficient products, technologies, and services
Time Discounting	• Bulk procurement and purchases (York et al., 2017) • Consider life-cycle cost analysis in decision-making (Shamshoian et al., 2005)	• Increase demand quickly and seek lower prices due to economies of scale • Life-cycle cost analysis can allow for the inclusion of energy price volatility, non-energy benefits, and product disposal
Low EE Salience in IT Staff	• Institutionalize the change within the C-suite (Schuetz et al., 2013) • Certification and professional recognition (York et al., 2017) • Reference best practices guides (York et al., 2017) ●●●Labeling (York et al., 2017)	• Lasting change and project success are correlated with the degree to which change management is institutionalized within the IT organization's policies and culture • Increase awareness of and expertise in working with energy-efficient products, technologies, and services • Create customer awareness of differences in EE among targeted products
Technical Risk Aversion	• Demonstration products and customer testimonials (York et al., 2017) • Educate other stakeholders as to how EE actions can improve reliability and resiliency, and reduce O&M costs (Lawrence Berkeley National Lab, 2020) • Initially prioritize low-risk measures (Lawrence Berkeley National Lab, 2020)	• Increase confidence in performance of products • Demonstrate a multitude of benefits from the EE measure • Demonstrate a proven process for implementing measures
Lack of Knowledge, Bounded Rationality	• Mass advertising (York et al., 2017)	• Increase awareness of products • Increase awareness of and expertise in working with energy-efficient products, technologies, and services
Time Discounting	• Bulk procurement and purchases (York et al., 2017) • Consider life-cycle cost analysis in decision-making (Shamshoian et al., 2005)	• Increase demand quickly and seek lower prices due to economies of scale • Life-cycle cost analysis can allow for the inclusion of energy price volatility, non-energy benefits, and product disposal

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Data availability The library of sources reviewed in this research is publicly available in a Zotero library, accessible at https://www.zotero.org/groups/4538694/organizational_and_psychological_measures_for_data_center_energy_efficiency_references.

Declarations

Competing interests The authors declare no competing interests.

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