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Cognitive Barriers During Monitoring-Based Commissioning of Buildings

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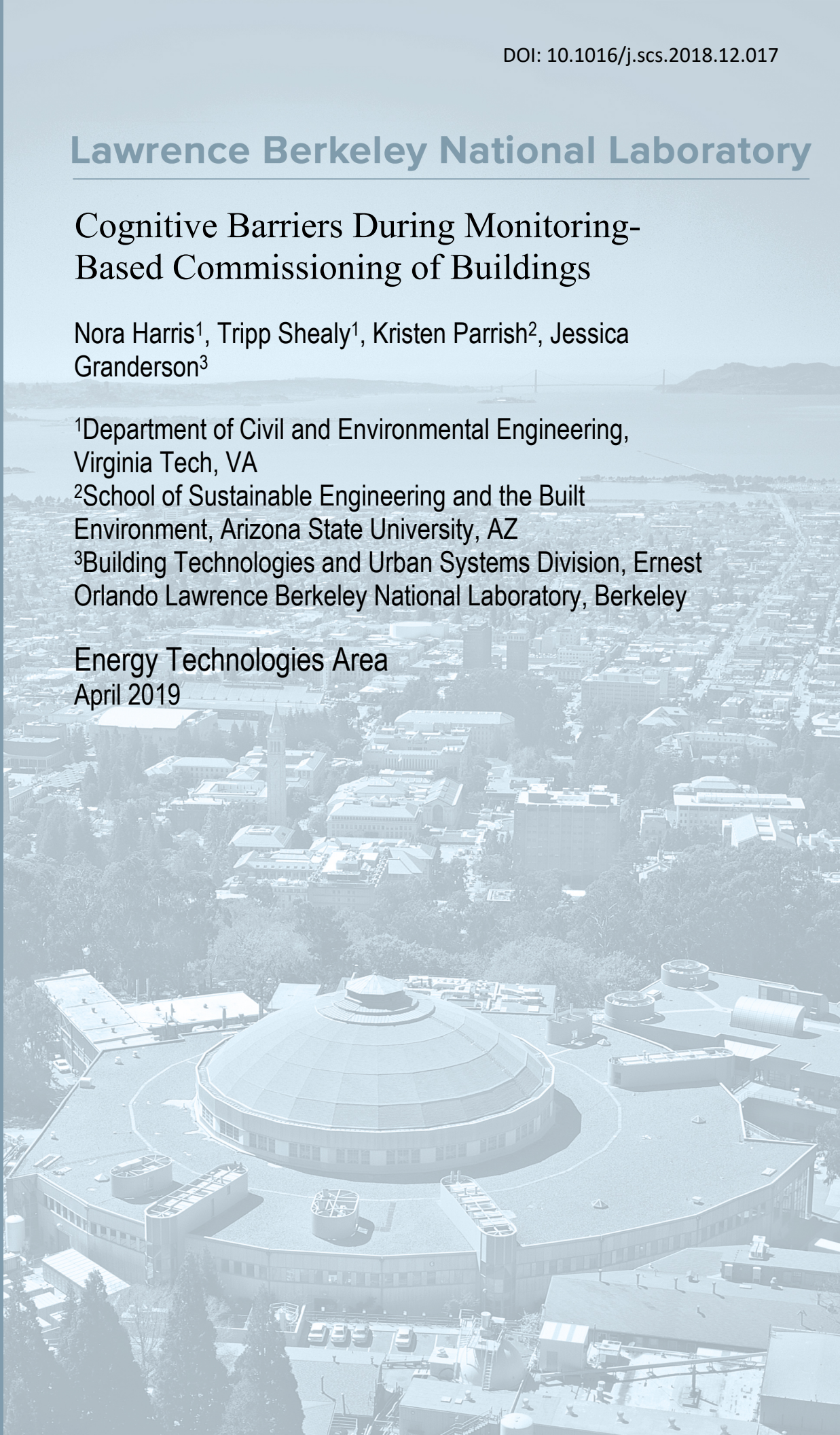

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Cognitive Barriers During Monitoring-Based Commissioning of Buildings

Abstract: Monitoring-based commissioning (MBCx) is a continuous building energy management process used to optimize energy performance in buildings. Although monitoring-based commissioning (MBCx) can reduce energy waste by up to 20%, many buildings still underperform due to issues such as unnoticed system faults and inefficient operational procedures. While there are technical barriers that impede the MBCx process, such as data quality, the focuses of this paper are the non-technical, behavioral and organizational, barriers that contribute to issues initiating and implementing MBCx. In particular, this paper discusses cognitive biases, which can lead to suboptimal outcomes in energy efficiency decisions, resulting in missed opportunities for energy savings. This paper provides evidence of cognitive biases in decisions during the MBCx process using qualitative data from over 40 public and private sector organizations. The results describe barriers resulting from cognitive biases, listed in descending order of occurrence, including: risk aversion, social norms, choice overload, status quo bias, information overload, professional bias, and temporal discounting. Building practitioners can use these results to better understand potential cognitive biases, in turn allowing them to establish best practices and make more informed decisions. Researchers can use these results to empirically test specific decision interventions and facilitate more energy efficient decisions.

Keywords: Monitoring-based Commissioning; Energy Management and Information Systems; Cognitive Biases; Behavioral Decision Science; Risk Aversion

1.0 Introduction

Buildings are one of the biggest contributing factors to energy use in cities, making them a target for urban energy reduction (Barnes & Parrish, 2016; Deetjen et al., 2018). Existing commercial buildings make up a large portion of the building stock in cities and can habitually underperform due to issues such as unnoticed system faults and inefficient operational procedures resulting in preventable energy waste (Mills, 2011). Monitoring-based commissioning (MBCx) is a continuous building energy management process that allows for the identification and resolution of this energy waste. MBCx leverages energy management and information systems (EMIS) technologies such as building automation systems (BAS), fault detection and diagnostic (FDD)

tools, and energy information systems (EIS) that collect and analyze energy data to facilitate targeted and persistent energy savings measures (Brown, Anderson, & Harris, 2006; Kramer, Crowe, & Granderson, 2017; Mills & Mathew, 2014). MBCx can be described as a continuous decision support system for energy demand reduction (Hutchins, 2016; Mills & Mathew, 2014). On a large scale, MBCx contributes to smart cities through the continuous monitoring process, real-time data, and improved energy performance (Brown et al., 2006).

The MBCx process has been shown to reduce up to 20% of a building's energy use (Granderson and Lin 2016). Additional studies demonstrate nearly 10-30% in gas savings (Granderson, Piette, & Ghatikar, 2011; Motegi et al., 2003). However, an energy efficiency gap, that is, a gap between savings potential and observed savings, still exists for many commercial buildings despite the availability of technologies to support MBCx, and documented case studies of their effective use (Fernandes, et al., In Press; Granderson & Lin, 2016; Granderson, Piette, & Ghatikar, 2011; Mills & Mathew, 2014; Motegi, et al., 2003). This gap in savings in largely due to social and behavioral challenges in MBCx implementation and can be attributed to irrationalities in human decision-making (Wilson & Dowlatabadi, 2007).

To help address the energy efficiency gap, this research uses a behavioral decision science perspective to better understand organizational decision making that often slows or halts the implementation of MBCx. Prior research investigates MBCx from a technological point of view (Granderson, Piette, & Ghatikar, 2011; Harris et al., 2018; Smith et al., 2011) and more broadly energy reduction from a normative perspective (e.g. optimization, utility theory) (Henderson & Waltner, 2013). Applying a behavioral science framework, helps to understand how cognitive biases inform judgement, and can explain the irrationalities that contribute to energy waste in buildings. For example, temporal discounting is a cognitive bias that leads to decision-makers placing more value on immediate consequences and discounting future rewards (Frederick et al., 2002; Green et al., 1994). Facility managers refraining from energy efficient investments even when payback periods are certain is an occurrence of temporal discounting where the focus is only on upfront cost (DeCanio, 1993; Delgado, 2017). Using a descriptive approach can account for these irrationalities and contribute to theoretical and practical advances that not only improve

understanding about how and why certain decisions are made but offer solutions to overcome these biases to enhance energy efficiency in buildings.

The goal of the paper is to provide building stakeholders (e.g., building owners, building engineers, facility mangers) with knowledge of specific cognitive biases that influence similar decision makers under comparable conditions and could impact their future decisions; in turn, helping these stakeholders predict cognitive obstacles and overcome them to further maximize energy efficiency. By better understanding the full range of cognitive biases, behavioral science and energy efficiency researchers can use this paper to begin developing empirical studies to test specific decision interventions for cognitive biases identified in the results of this study. The results presented in this paper open a new avenue of inter-disciplinary research for those who study the energy efficiency gap in buildings and offer a new application of research for those who study behavioral decision science (Delgado & Shealy, 2018).

The background section describes previous research that reveals barriers to MBCx and how some of these barriers can be explained by understanding the link between behavioral decision science research and energy efficiency decisions. The research objective and methodology follow, with a presentation of the resulting cognitive biases that emerged from the qualitative data. The results demonstrate that many cognitive biases impact decisions during MBCx, highlighting that barriers to energy savings are not only technical, but also behavioral. Potential behavioral interventions to help overcome the defined cognitive biases are discussed, and suggestions for future research are provided.

2.0 Background and Theory

Previous research describes some commonly experienced technical barriers faced by organizations during the monitoring-based commissioning (MBCx) process such as data configuration and quality. In a study of over 40 organizations using MBCx, Harris et al. (2018) found data configuration to be the top barrier. Organizations frequently experienced issues integrating data from hardware, such as submeters, into energy management and information systems (EMIS) due to things like legacy building automation systems (BAS) or information technology (IT) issues such as data security. Energy management and information systems

(EMIS) offer the capability to collect, analyze, and sometimes control, building energy use through hardware and software (Consortium for Energy Efficiency, 2012; King & Perry, 2017). Some type of EMIS technology is needed to conduct monitoring-based commissioning. That may be a building automation system (BAS) to manually analyze operational trend log data, an energy information system (EIS) to analyze and visualize whole building and sub-metered energy use, or an automated fault detection and diagnostic (FDD) tool. In a case study, University of California, Merced reported one of the biggest issues with using BAS as their EMIS analysis tool had to do with data quality; network and connectivity problems led to false alarms, which then required "significant resources" to validate the data (Granderson et al., 2011).

Although it is important for practitioners to understand technical barriers, there is less focus on the challenges that are caused by human behavior and decision making. For example, a case study about Wal-Mart noted that the EMIS did not include some desired features, such as benchmarking, which required exporting the data from the EMIS, for external analysis (Granderson et al., 2011). This begs the question, could the issue have been avoided? Was there a decision earlier in the process that led to improper selection of EMIS?

An energy management initiative for three multi-tenant office buildings in Washington, DC employed consulting and advisory services for configuration of their EMIS, including meter installation, web interface development, and HVAC monitoring and alert services (Henderson & Waltner, 2013). However, the authors pointed out that there was "little evidence" that the building engineers used the web interface set up by the consultants. Why would building engineers not use the EMIS that was intended to provide data for more informed decisions? The technology was in place, and seemingly the most capital-intensive phase was complete, yet decisions to take corrective action towards energy savings still did not occur.

Behavioral decision science can provide insight into why such inaction among building engineers would persist even after installing EMIS and going through the MBCx process. Issues in the decision-making process, likely inhibit more pervasive uptake of MBCx processes in commercial building energy management. This paper examines these barriers to MBCx using a

behavioral decision science perspective to better understand the origins of these seemingly irrational decisions, or inaction to decide.

2.1 Behavioral models of decision making

According to traditional economic models of decision making, individuals are expected to choose the option that maximizes utility, or leads to the outcome that has the most benefit. However, behavioral decision science research demonstrates that individuals routinely make irrational decisions, especially when faced with uncertainties, leading to outcomes that do not maximize utility (Camerer, Loewenstein, & Rabin, 2011; Khaneman & Tversky, 1979). For example, sustainable operations and maintenance practices, such as MBCx, can reduce operating costs over time and provide additional benefits such as improved occupant comfort and productivity. Still, organizations often undervalue these practices due to a focus on first cost and failure to consider life cycle cost and long-term payback (Hodges, 2005).

Behavioral models of decision making, such as bounded rationality, can help explain irrational decisions. Bounded rationality accounts for limitations of human cognition such as thinking capacity, information, and time, leading individuals to attempt to simplify the decision environment through the use of heuristics, which serve as mental short cuts (Simon, 1982). Although heuristics do not always lead to negative outcomes and can help accelerate decisions (Gigerenzer et al., 1999), they can make the decision maker more susceptible to cognitive biases (Tversky & Kahneman, 1975). Cognitive biases are a systematic deviation in judgment from formal logic, often leading to irrational decisions (Ariely, 2008). The decision environment or context can determine the particular cognitive bias or heuristic that will impact the judgment of the individual (Hilbert, 2012).

Figure 1 explains the relationship between the major concepts of behavioral models of decision making, behavioral decision science concepts (cognitive biases), energy efficiency (specifically MBCx), and decision interventions. The current process outlined in black in Figure 1 emphasizes that bounded rationality leads to cognitive short cuts, or heuristics, and, just like other decision makers, these heuristics can influence building managers judgement. By understanding what heuristics are frequently used during the decision making process for

building energy performance, researchers can begin to test interventions for corrective models of decision making that lead to more optimal outcomes.

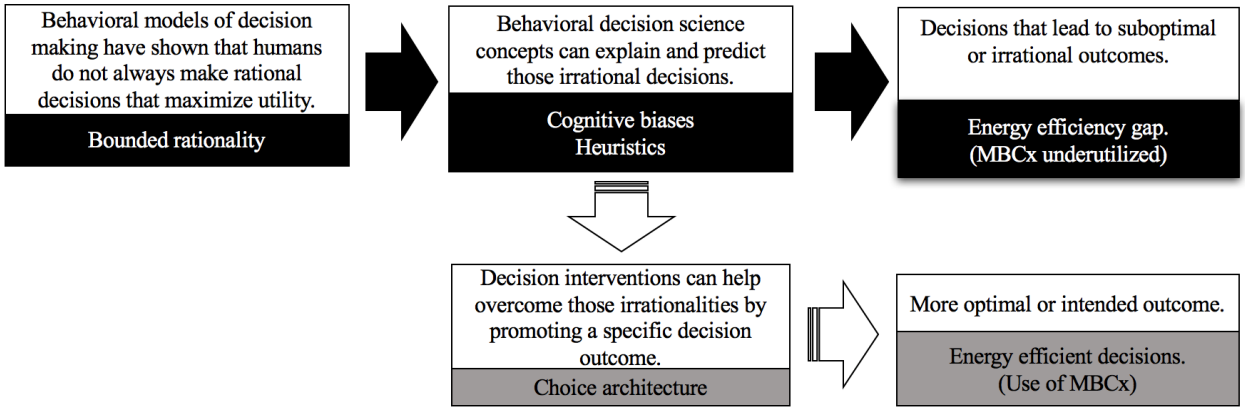

Figure 1. Application of behavioral decision science to monitoring based commissioning can lead to more optimal and energy efficient decisions

2.2 Examples of cognitive biases in energy decisions

This section offers definitions and examples of cognitive biases from previous behavioral decision science research focusing on decisions involving energy efficiency. The purpose here is to provide concrete evidence of the relationship between cognitive biases and decisions about energy. The expectation is that cognitive biases similarly impact MBCx decision making. While issues of cost and time are certainly barriers to MBCx these issues can often represent symptoms to underlying root problems in cognitive processing capabilities. For instance, the future utility of financial savings of MBCx can be upwards of 20% annually (Granderson and Lin 2016), but this requires an upfront investment. In this scenario cost can be expressed as a barrier through a myopic point of view. In other words, future gains from energy performance are often implicitly discounted compared to the immediate losses from the initial investment. Behavioral decision science refers to this type of thinking as temporal discounting, where future benefit is undervalued for immediate reward (Caney, 2014; S. Frederick, Loewenstein, & O'donoghue, 2002; Gattig & Hendrickx, 2007).

This is just one example of how cognitive biases can influence energy decisions. Other cognitive biases that emerged in the results include: choice overload, information overload, risk aversion,

social norms, professional bias, and status quo bias. These particular biases and their theoretical understanding are highlighted in the section below.

2.2.1 Choice overload

Choice overload occurs when an individual is presented with a wide array of options that vary along multiple attributes. Choice overload makes it difficult for an individual to evaluate alternatives due to increased cognitive effort, which can lead to dissatisfaction when a decision is made (Iyengar & Lepper, 2000) or not making a choice at all (Dhar, 1997). Muthulingam et al. (Muthulingam, Corbett, Benartzi, & Oppenheim, 2013) found that adding more options to a list of energy saving recommendations does not necessarily impact the number of recommendations pursued; rather, they found a modest negative impact on the overall energy savings.

2.2.2 Information overload

Similar to choice overload, information overload can negatively impact decision-making (Edmunds & Morris, 2000) and occurs when an individual is presented with excessive information, leading to inability to process the information due to cognitive limitations, or time constraints (Eppler & Mengis, 2004). With the advent of smart-meters technologies that can provide private households with detailed energy consumption information, information overload is a concern for the design of the energy display (Dalén & Krämer, 2017; Dalén, Krämer, & Weinhardt, 2013). Energy displays can encourage residents to reduce or shift the time of their energy use (Darby, 2008), but too much information on a display can potentially reduce its effectiveness by unnecessarily increasing complexity.

2.2.3 Risk aversion

Risk aversion explains why a decision maker is less likely to accept risk when the outcome is framed as a gain in value, but more likely to accept risk when the outcome is framed as a potential loss in value (Khaneman & Tversky, 1979; Tversky & Kahneman, 1992). Risk aversion can predict how homeowners selling in a down market may insist on a higher asking price (Genesove & Mayer, 2001), why investors sell profitable stocks too soon and retain losing stocks too long (Odean, 1998), and why consumers generally hold failing assets longer than winning assets (Carmon & Ariely, 2000; Cummings, Brookshire, Bishop, & Arrow, 1986; Knetsch,

1989). Related to energy, risk aversion has been suggested as an explanation for the slow adoption of new energy efficient technologies. For example, Farsi (Farsi, 2010) found that residents showed a greater degree of risk aversion when considering energy efficient insulation and ventilation systems, in comparison to traditional products, suggesting the potential energy savings and resulting increase in comfort are undervalued.

2.2.4 Temporal discounting

Temporal discounting examines the value individuals place on rewards over time and reveals that to a certain extent, individuals place more value on immediate rewards than future rewards (Shane Frederick et al., 2002; Green et al., 1994). Temporal discounting surfaces in energy decisions when management refrains from energy efficient investments even when payback periods are certain because they focus on the upfront cost (DeCanio, 1993; L. A. Delgado, 2017). Bounded rationality can explain this shortsightedness in management decisions about energy-efficiency (DeCanio, 1993).

2.2.5 Social norms

Social norms are generally accepted expectations of behaviors or attitudes that are approved or disapproved of within a group or society (Elster, 1989). An individual's behavior and decisions can be influenced by their perceptions of social norms and can be dependent on the specific situation (Samson, 2017). For example, an energy conservation program through the company OPOWER encouraged households to reduce their energy use by comparing them to their neighbors, effectively influencing their perception of social norms (Allcott, 2011).

2.2.6 Professional bias

Professional bias occurs when an individual has a narrowed perspective based on the conventions of one's profession (Linder, 1987). Similar to social norms, professional bias can influence an individual's behavior based on their perceptions of what is generally accepted in a particular field of practice. For example, mechanical engineers are typically tasked with designing a system to meet cooling needs in building design and commonly oversize HVAC systems, leading to a greater amount of energy use than necessary (Reddy & Claridge, 1993; Woradechjumroen, Yu, Li, Yu, & Yang, 2014).

2.2.7 Status quo bias

Status quo bias is the tendency of decision makers to prefer maintaining previous decisions, circumstances, or processes even if an alternative decision could potentially increase utility or benefit (Samuelson & Zeckhauser, 1988). The "default" option for a decision could be considered the status quo. Changes to the default can significantly influence the outcome of decisions, meaning, decision makers are likely to maintain the default suggestion (Johnson & Goldstein, 2004). When electricity suppliers that use renewable energy sources were presented as the default option, consumers were more likely to choose renewable energy sources as opposed to 'grey' electricity sources like coal (Pichert & Katsikopoulos, 2008).

3.0 Research objective

The objective of this research was to identify how cognitive biases impede the MBCx process throughout its planning, configuration, implementation, and continued use through the analysis of a unique dataset of direct responses from organizations using MBCx and reporting issues in real time. By identifying which cognitive biases exist, practitioners can become more aware of their own, and their colleagues' biases and begin to address these explicitly, in turn supporting more energy efficient decisions. For example, facility managers might understand that MBCx offers long term benefits, but their management team might exhibit temporal discounting, focusing exclusively on short-term costs. Recognizing this bias ahead of time, facility managers can focus their business case on long-term gains and encourage management to make a more energy-efficient and cost-effective decision. This research promotes awareness of these cognitive biases throughout the MBCx process in order to create a more holistic picture of the potential barriers to MBCx, as well as provide potential solutions and encourage interdisciplinary research to find solutions that interlink technical and nontechnical barriers.

4.0 Research methodology

This section details the research population, qualitative data, and the steps followed to identify the cognitive biases in the MBCx process.

4.1 Research population

The data for this paper comes from the Smart Energy Analytics Campaign ("About the Smart Energy Analytics Campaign," 2017), an initiative with aims to increase the adoption of energy management practices that leverage EMIS technologies by providing participants with technical assistance, best practices, case studies, and providing an outlet for success stories. At the time of data collection for this paper, there were 42 organizations participating in the campaign, including higher education (31%), office (36%), laboratory (10%), hospital (10%), retail (5%), grocery (3%), healthcare (3%), and hospitality (3%).

4.2 Original qualitative dataset

The specific data used in this study came from interview and survey responses from organizations that participated in the Campaign. Interview data was recorded by a Lawrence Berkeley National Laboratory (LBNL) researcher during phone interviews with participants. Surveys were completed via self-report by participants through a web-based form. This paper uses both the interview data and open-response survey questions, resulting in a purely qualitative data set. All data was anonymized prior to analysis and was not identifiable to specific participants. The select questions used in this study, the reporting method, and number of responses are shown in Table 1.

Table 1. Interview and survey questions used for data analysis

Reporting Method	Specific Question	# Responses
Phone interview; researcher recorded organization's responses	What are your biggest challenges in meeting your plans?	41
	Please give us an overview of your current data collection, any software you use, and your process for using data to support facility operation (data source, data frequency, which type of software).	42
Organization request for technical assistance; researcher recorded organization's request	Documentation of technical assistance identified.	90

Web survey: organization self -reports	Please describe how you used your EMIS.	22
Web survey: organization self -reports	Describe your EMIS installation: Indicate the types of data points included, the automated analysis included, and any other characteristics you'd like to share	9
Web survey: organization self -reports	Planning for EMIS: How did you decide what EMIS features were critical? How did you create the business case for funding EMIS?	9
Web survey: organization self -reports	Ongoing energy management: Describe the energy management process you used to analyze information from the EMIS, identify opportunities, and take corrective actions.	9

4.3 Qualitative data narrowed to elements classified as barriers

The qualitative data outlined in Table 1, was decomposed into 395 elements, with each element containing one principal concept. Each element was then classified as a barrier, enabler, or neutral. For example, the following element "*There is no structured engagement or process to manage the energy information system (EIS)*," was marked as a barrier because it was a response to the question "*What are your biggest challenges in meeting your plans?*" The elements classified as barriers, neutral, and enablers were completed independently by two coders. Discrepancies in the classification were then discussed between coders and classifications were chosen based on a mutually agreed decision. This paper uses the 185 elements that were classified as barriers. These 185 elements were then reviewed by three coders to identify emergent cognitive biases as detailed in the next steps. The approach to classify concepts into elements is similar to other prior approaches in qualitative data analysis (e.g. Blizzard & Klotz, 2012; Harris et al., 2018)

4.4 Specific cognitive biases selected to create a codebook

The process of developing a codebook was modeled after a qualitative data coding method from Bailey (2017). Three coders, referred to as coder 1, coder 2, and coder 3, collaborated on the

qualitative data coding. The coders were all familiar with energy management and behavioral decision science concepts and each have previous publications bridging these disciplines. To determine the specific cognitive biases used for the data analysis, coder 1 reviewed an in-depth list of behavioral decision science concepts, listed in the *Behavioral Economics Guide 2017* (Samson, 2017). More than fifty possible cognitive biases were available for reference. Using the 185 elements classified as barriers, coder 1 then completed an initial scan of the elements to determine which cognitive biases were manifested in the data and found evidence of the following: choice overload, risk aversion, temporal discounting, status quo bias, and social norms. After discussion with coder 2 and 3, and initial attempts at coding, professional bias and information overload were added. The coders also added the option of *none* for those elements that did not have any evidence of cognitive biases and the option *other* for elements that did not fit clearly within one of the predetermined barriers and needed to be discussed between all coders. The finalized codebook contained 7 cognitive biases, *none,* and *other* as options for coding the elements.

4.5 *Elements were coded with the codebook by the three coders*

The three coders coded all 185 elements with the finalized list of cognitive biases based on the previous step. They were instructed to review the elements and refer to the definitions for each of the specified biases. The 3 coders then discussed those elements with discrepancies, or marked as *other*, and agreed upon a final code for the respective elements. Coding examples and rationale are listed in Table 2. This process of using a codebook by multiple coders is based on prior methods in qualitative research (e.g. see Saldana, 2015).

Table 2. Examples of cognitive bias coding

Element	**Cognitive Bias**	**Rationale**
"2-year simple payback threshold for management funding of projects"	temporal discounting	Requirement upholds a short-term view, which leads to discounting of future returns from energy-efficient decisions

"Should the RFP specify the back end or allow for multiple back-ends; should the RFP request their rules, so that owner can know if applicable?"	choice overload	Participant was confronted with a flood of choices when attempting to develop a request for proposal (RFP) for an EMIS leading to many questions
"[It is challenging] getting people to use the systems. The operators just put the BAS into manual or override."	professional bias	Operators were resisting using the new EMIS as it is not a technology that is conventionally used in their profession
"We don't have insights into what others owners are doing with their EMIS and how they stack up. Would be helpful to get more information for their business case"	social norms	Participant wants to better understand what others are doing, i.e. what behavior is accepted when using EMIS
"Keeping up with things that break"	none	Lack of evidence of context for cognitive bias

5.0 Results

The results of the qualitative data coding process provide evidence of cognitive biases acting as barriers to the MBCx process. Table 3 summarizes the number of times each of the emergent cognitive biases occurred within the data, in descending order. There was evidence of cognitive bias in 30% of the elements. For a summary of the barriers without cognitive biases, see Harris et al., (2018). In the next section, examples of practical solutions to overcome these biases are suggested.

Table 3. Cognitive biases exhibited in qualitative data

Cognitive biases	# Elements
Risk Aversion	13
Social Norms	10
Choice Overload	10
Status Quo Bias	8
Information Overload	8

Professional Bias	4
Temporal Discounting	3
# of Elements with evidence of cognitive bias	56
Total # of Elements	185
% of Elements with evidence of cognitive bias	30%

The results are outlined in descending order of occurrence for clarity, but it is important to note the synergies between the cognitive biases. Risk aversion and temporal discounting both describe difficulty gaining buy-in due to skewed investment perspectives. Social norms, status quo bias, and professional bias are all related to the resistance of change. Choice overload and information overload are both caused by a decision makers inability to completely process information. These synergies also lead to the nuances between the cognitive biases that are discussed further in the limitations.

The highest occurring cognitive bias was risk aversion (occurring 13 times). Participants had issues gaining buy-in from management and receiving approval to pursue MBCx or specific energy conservation measures identified through the MBCx process, specifically when there was uncertainty related to the monetary savings. In one case, a participant was solely interested in EMIS vendors/services providers that offer guaranteed savings, meaning, the participant was aiming to reduce any potential risk. Although previous case studies have validated the savings offered through MBCx, participants (or their management) were still hesitant.

The second-most common cognitive bias was social norms, which emerged 10 times. As MBCx is a somewhat new process, social norms can help explain why participants were having difficultly institutionalizing the process. For example, an organization felt that their "client [was] behind the curve on energy and sustainability culture," showing how social norms related to MBCx are perceived as being in transition. Organizations are still unsure of what is expected of them regarding energy efficiency decisions, asking specifically for "insights on what other owners are doing with their EMIS and how [they] stack up… that what [they] are doing is appropriate." Evidence of social norms was also found in relation to occupant behavior. Two participants were interested in developing publicly facing EMIS dashboards in hopes to engage occupants in energy saving behavior; essentially using the dashboard as a tool to change the

social norms of occupants. The participant asked questions like, “What’s most persuasive to non-energy people?” and “What might change their behavior?” Instead of the generally accepted attitude of unaffectedness towards building energy use, participants hoped occupants would visually see how their behavior is having an impact and lead to a sense of responsibility.

Choice overload emerged 10 times. The most common issue was mainly related to participants selecting an EMIS that would best fit their needs. With an abundance of EMIS vendors and varying features, participants were overwhelmed by EMIS options. In one case a participant asked, “Should the RFP specify the back-end or allow for multiple back-ends? Should the RFP request specific rules to know if the EMIS is applicable?” Another participant was looking specifically for “small retail options for EMIS.” These participants requested technical assistance to develop specifications for RFPs and review submittals to make an informed decision.

Information overload appeared 8 times. Responses related to information overload were always related to the data made available by EMIS. Participants struggled to manage the volume of data and get value out of the information. The ability, or inability to synthesize information led to issues such as difficulty “prioritizing faults” that were identified by EMIS.

With status quo bias occurring 8 times, participants were failing to get the full value out of their EMIS, by simply relying on existing processes, or having difficulty establishing new processes to engage with the EMIS. In one case, a participant had successfully installed EMIS, allowing them the capability to access “daily or monthly energy consumption”, but “people [were not] doing anything with the data”, essentially rendering the EMIS useless.

Professional bias appeared 4 times, when participants reported that some of their specific team members, such as operations staff, resisted buying into the use of EMIS as it was not conventionally expected as a part of their role.

Temporal discounting emerged 3 times. It is similar to risk aversion, where participants had difficulty gaining buy-in due to shortsightedness demonstrated by management with simple payback thresholds or return on investments of 2 years or less. The next section makes

suggestions on how to use decision interventions to help overcome these cognitive biases with aims to translate into future research.

6.0 Discussion

Although there are many technical barriers to MBCx, the results show that nearly one third (30%) of the barriers faced by the cohort are due to cognitive processing capabilities. One way to mitigate these cognitive biases, or barriers, is through the use of decision interventions. Choice architecture is a type of decision intervention used to shape the decision environment. When designing a decision, there is no neutral choice architecture, meaning, some options must be first, attributes are or are not presented, and these factors are likely to influence decisions about MBCx (Thaler & Sunstein, 2008). This section provides examples of specific interventions that can be used to overcome or reduce the effects of the emergent cognitive biases from the results. For a more in-depth list of choice architecture tools, see Johnson et al. (2012) or Thaler and Sunstein (2008).

Risk aversion, the cognitive barrier that appeared most, is caused by risk and uncertainty of decision outcomes. Framing is a form of choice architecture where the decision is framed intentionally as a loss or gain. Framing can significantly influence choice and is replicated in domains such infrastructure design (Shealy et al.,, 2016), healthcare (Malenka, et al., 1993; Marteau, 1989), and climate change (Gifford & Comeau, 2011; Morton et al., 2011). Since decision makers are more likely to take action in order to avoid potential losses (as opposed to qualifying for potential gains), instead of framing the business case for MBCx as the potential to save 20% on energy costs, the choice architect, often a facility staff member or energy management team staff member, should frame the decision to show how the organization is currently overspending on energy by 20% (Todd & Houde, 2011). Simply reframing the choice requires no additional technological or monetary investment and can have a big effect. When decision makers are already losing they are more likely to become risk seeking (Farsi, 2010; Shealy & Klotz, 2015).

Influencing social norms is another way to encourage the adoption and use of MBCx. If organizations see that their peers have been successful in saving energy using MBCx, they may

likely be motivated to uphold that social norm and save energy themselves. Simply comparing energy use between neighbors (Laskey & Kavazovic, 2010), and telling residents that their neighbors were conserving energy (Nolan et el., 2008), led to a 2% and 9% reduction in energy use, respectively. Another way to influence social norms is through the use of a social reference, such as a role model. Professional engineers given a "role model" project that reached high levels of sustainability, increased engineers' consideration for sustainability in their own designs by more than 30% (Harris, Shealy, & Klotz, 2016). Related to MBCx, the choice architect could change perceived social norms through peer groups from different organization types that focus on successes and strategies for using MBCx. The Smart Energy Analytics campaign encourages this through peer-to-peer exchange ("About the Smart Energy Analytics Campaign," 2017). Successful peers can motivate others to reach similar high achieving energy saving goals. This type of peer-to-peer network requires little technological or financial investment and the Smart Energy Analytics campaign is readily available for practitioners to participate.

Choice overload, experienced by organizations when choosing an energy management information system (EMIS), can be reduced by "collaborative filtering" (Thaler & Sunstein, 2008). Collaborative filtering takes advantage of choices made by individuals with similar interests (Thaler & Sunstein, 2008). So, the choice architect helping organizations unsure of the best EMIS selection could use information about which EMIS worked well for peer organizations with similar size, type, and goals to improve decision making.

Information overload is cognitively similar to choice overload in that information, like choices, can exceed processing capacity among decision makers and lead to neglecting critical attributes or options. Information related to EMIS data was a particular issue that emerged from the results. Participants mentioned struggling to manage the volume of data and how to get value out of this information. An approach to help decision makers reduce information overload is through prioritization, or weighting, what information is most critical to help them take action. Filters imbedded in EMIS to hide non-essential data is one approach. Another, less technical approach is through checklists. Checklists can be helpful in promoting consideration of latent values that otherwise can get lost in the amount of data being collected (Gawande, 2011).

These are just some examples of decision interventions that can help overcome cognitive biases experienced during MBCx. Future research can empirically test these examples to determine their impact on the MBCx process, whether or not they are sustained over time, and their impact on different organization types. Necessary to note, choice architecture is not fail proof and can have varying degrees of impact depending on individual differences (Johnson et al., 2012). Therefore, future research can also focus on determining which roles in organizations are more likely to be affected by these biases and designing more targeted decision interventions.

Future research can also continue to evaluate the MBCx process for the existence of cognitive biases. As mentioned, the researchers attempted to determine the most relevant cognitive biases, but these interpretations are not infallible. Cognitive biases may also impact other stakeholders in the MBCx process such as vendors or professional organizations. A deeper understanding of these cognitive biases allows for the design of more effective interventions for a wider variety of MBCx stakeholders. These interventions can be empirically tested by researchers and compared across various stakeholder groups. For example, vendors can focus on ways to make it easier for organizations to overcome choice overload when selecting an EMIS technology by creating standard ways to compare between features. The point of this research is not to downplay purely technical barriers to MBCx, but to promote awareness that nontechnical barriers, especially limitations in cognitive processing capabilities and the resulting biases, can prevent MBCx from being pursued altogether.

6.1 Limitations

The organizations from the data were at different phases in the MBCx process, meaning, the data captured may not represent the phases of the process equally. For example, although the organizations that elected to participate in the Smart Energy Analytics Campaign have some type of EMIS, some were not yet carrying out an intentional MBCx process. Since qualitative data coding for cognitive biases is somewhat subjective, this paper aimed to reduce subjectivity with 3 different coders that discussed any discrepancies. However, there was still potential for misinterpretation, even though an agreement was reached between coders. For example, both status quo bias and professional bias are related to resistance to change, therefore the nuances between the two were difficult to discern in some of the data without specific organizational

context. Furthermore, this data was reviewed post data collection, therefore the context was difficult to determine, leading many elements to be classified as “none”.

7.0 Conclusion

This paper extends the current understanding about the monitoring-based commissioning (MBCx) process by making connections between behavioral models of decision making, choice architecture, and energy efficiency decisions. This paper identifies specific cognitive biases during the decision-making processes related to the implementation and use of MBCx. The results can be used by practitioners, such as facility managers, building engineers, or energy managers, to prepare for the negative impact cognitive biases can have on decisions for energy efficiency. Practitioners can then incorporate choice architecture tools or other decision interventions when constructing how to present the business case or when soliciting and selecting the energy management information system (EMIS).

Researchers can use these results as justification for specific cognitive biases and decision interventions to improve energy performance in buildings. For example, development of choice architecture tools to help overcome risk aversion is a logical priority for making the business case for MBCx because risk aversion was the highest occurring barrier for organizations. Being aware of the tendency to be risk averse can help practitioners and researchers assess whether this aversion is intentional and necessary. Ultimately, this research intends to promote awareness of cognitive biases in MBCx. Future research at the intersection of behavioral decision science and energy efficiency can lead to more empirically tested decision interventions and choice architecture tools producing more energy efficient buildings. By better understanding the full range of judgment and decisions that must be made by MBCx users, future research can search for ways to turn cognitive obstacles into opportunities.

The research presented in this paper offers a more complete understanding of the types of decisions being made by building managers and offers intentional changes to decision environments, which are relatively low-cost interventions compared with new technologies or incentives (Benartzi et al., 2017; National Academies of Sciences and Engineering, 2017). Intentionally setting up decision environments is well studied and improving practice in fields

from medicine (Johnson & Goldstein, 2003) to finance (Fox & Langer, 2005), to insurance (Johnson, 1993). Similar advances are now possible to improve energy performance in buildings.

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