Barriers and Cognitive Biases in the Monitoring-Based Commissioning Process

Nora Harris

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Tripp Shealy, Chair
Georg Reichard
Kristen D. Parrish

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ABSTRACT

Many buildings underperform leading to up to 20% energy waste. Case studies on monitoring-based commissioning (MBCx) have shown that using energy management and information systems (EMIS) for continuous energy monitoring and analysis enables the identification of issues that cause energy waste and verifies energy conservation measures. However, MBCx is underutilized by organizations leading to an energy efficiency gap between the energy saving potential of technologies like EMIS and observed savings. This energy efficiency gap can be attributed to general barriers to MBCx and barriers caused specifically by cognitive bias in the decision-making process. Using qualitative data from over 40 organizations implementing and practicing MBCx, this manuscript provides a better understanding of these barriers. Chapter 1 synthesizes and codes the qualitative data to develop a framework of variables acting as barriers and enablers to MBCx. The framework highlights commonly experienced barriers like data configuration, and also variables with conflicting results like payback/return on investment, which was experienced as a barrier to some organizations and enabler to others. Chapter 2 examines the barriers to MBCx through a behavioral decision science lens and finds evidence of cognitive biases, specifically, risk aversion, social norms, choice overload, status quo bias, information overload, professional bias, and temporal discounting. The success of choice architecture in other energy efficiency decisions is used to offer suggestions for ways to overcome these cognitive biases. This manuscript can be used by practitioners to better understand potential barriers to MBCx and by researchers to prioritize gaps and find methods to overcome the barriers to MBCx.

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GENERAL AUDIENCE ABSTRACT

Buildings have the potential to save 20% of their energy use through the practice of monitoring-based commissioning (MBCx). MBCx involves continuous monitoring and analysis of a buildings energy use to quickly identify and resolve issues that cause energy waste. However, MBCx is underutilized due to technical and non-technical barriers. This manuscript uses qualitative data from over 40 organizations implementing and practicing MBCx to provides a better understanding of these barriers. Chapter 1 synthesizes and codes the qualitative data to develop a framework of variables acting as barriers and enablers to MBCx. The framework highlights commonly experienced barriers like data configuration, and also variables with conflicting results like payback/return on investment, which was experienced as a barrier to some organizations and enabler to others. Chapter 2 examines the barriers to MBCx through a behavioral decision science lens and finds evidence of cognitive biases, specifically, risk aversion, social norms, choice overload, status quo bias, information overload, professional bias, and temporal discounting. The success of choice architecture in other energy efficiency decisions is used to offer suggestions for ways to overcome these cognitive biases. This manuscript can be used by practitioners to better understand potential barriers to MBCx and by researchers to prioritize gaps and find methods to overcome the barriers to MBCx.

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ATTRIBUTION

This foreword describes the contribution of each of the authors for the two manuscripts within this thesis document.

Manuscript 1:

Nora Harris – Nora developed the concept for the research, reviewed the relevant literature, developed the methods, analyzed the data, and wrote all sections of the manuscript, incorporating comments and feedback from the other authors.

Tripp Shealy – Tripp helped to finalize the research concept and methods, completed data analysis, and offered multiple rounds of feedback and comments on the manuscript.

Hannah Kramer – Hannah collected initial data, completed data analysis, and offered feedback and comments on the manuscript.

Jessica Granderson – Jessica collected initial data and offered feedback and comments on the manuscript.

Georg Reichard – Georg completed data analysis and offered feedback and comments on the manuscript.

Manuscript 2:

Nora Harris – Nora developed the research concept and methods, reviewed the relevant literature, analyzed the data, and wrote the entirety of the manuscript, incorporating input from the other author, Tripp.

Tripp Shealy – Tripp provided input in order to finalize the research concept and methods, analyzed the data and provided multiple rounds of feedback and comments on the manuscript.

INTRODUCTION

Monitoring-based commissioning (MBCx) is more successful than periodic retro-commissioning in respect to maintaining energy savings, but there are still many barriers that organizations face when implementing or practicing MBCx. The focus of this research is to better understand the general barriers to MBCx and those barriers specifically related to cognitive biases in decision making. This research can be a starting point for practitioners who want to learn more about common experiences with MBCx, as it synthesizes the experience of over 40 organizations throughout the MBCx process. Researchers can use this research to identify commonly experienced barriers and use the information to prioritize research that focuses on ways to overcome these barriers.

This document contains two research papers that focus on barriers to monitoring-based commissioning. Chapter 1 is a research paper that explores the general barriers to MBCx by synthesizing the experience of over 40 organizations with the MBCx process. Chapter 1 points out barriers that are commonly experienced and organizes them into a framework. Chapter 1 highlights the need for more research needed to find enablers that can help overcome the identified barriers. Chapter 2 is a research paper that analyzes the barriers to MBCx with a behavioral decision science lens revealing the existence of cognitive biases to the MBCx process. These cognitive biases lead to irrational decision making that can impede the MBCx process and result in missed opportunities for energy savings. Decision interventions, in the form of choice architecture, are offered as a potential solution to cognitive biases in MBCx.

Journal Paper:
A Framework for Monitoring-Based Commissioning: Identifying Variables that Act as Barriers and Enablers to the Process

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Authors:
Nora Harris [a, *],

Tripp Shealy [a],

Hannah Kramer [b],

Jessica Granderson [b],

Georg Reichard [c]

a. Charles Edward Via, Jr., Department of Civil and Environmental Engineering, Virginia Tech, 200 Patton Hall, Blacksburg, VA 24061, USA
b. Building Technologies and Urban Systems Division, Ernest Orlando Lawrence Berkeley National Laboratory, 1 Cyclotron Rd, Berkeley, CA 94720, USA
c. Myers-Lawson, School of Construction, Virginia Tech, 410 Bishop-Favrao Hall, Blacksburg, VA, 24061, USA

*Correspondence: neharris@vt.edu

Abstract: The practice of monitoring-based commissioning (MBCx) using energy management and information systems (EMIS) has been shown to enable and help sustain up to 20% energy savings in buildings. Despite research that has quantified the costs, benefits, and energy savings of MBCx, the process remains under-utilized. To understand why MBCx is not more frequently adopted and how to encourage its use, this research synthesizes qualitative data from over 40 organizations, currently engaging in MBCx. The outcome of this research is a framework containing variables that emerged from the qualitative data, marked as barriers or enablers, organized by phases of the MBCx process. The framework is comprised of 51 emergent variables that fall within 13 different categories. The variables that most frequently act as barriers are *data - configuration, analysis & reporting – measurement & verification (M&V), EMIS – developing specifications*, and *IT - data architecture*. Although, some variables that act as barriers for one organization were identified as enablers for another. For example, *business case – payback/ROI* was considered a barrier 7 times and an enabler 3 times. One organization had difficulty making the business case for the initial investment for MBCx due to lack of cost information, while another was able to justify large investments with documented savings of previously implemented measures identified through MBCx. The framework formally validates barriers found in previous research, and can be used by practitioners to better understand common experiences with MBCx. This research highlights the need for a similar collective data set to validate common enablers to MBCx and also the need for empirical research to determine relationships between variables.

Keywords: Monitoring-based Commissioning; Framework; Energy Management and Information Systems; Information Systems; Commercial Buildings

1. Introduction

The process of monitoring-based commissioning (MBCx) can help sustain optimal energy performance in buildings, while maintaining occupant comfort (Brown et al. 2006; Piette et al. 2001; Granderson et al. 2011a). In the building efficiency literature, MBCx entails ongoing commissioning with the goal of continuous building performance improvement by way of data monitoring and analysis (Kramer et al. 2017; Mills and Mathew 2014). MBCx can enable the identification of otherwise untapped energy conservation measures and also verify the energy savings from the re-commissioning of existing equipment (Mills and Mathew 2014).

Alongside the evolution of MBCx there is the evolution of system monitoring technologies to support the process. Specifically, energy management and information systems (EMIS) enable and help sustain up to 20% site energy savings (Granderson and Lin 2016b). Many technologies fall under the umbrella term EMIS (e.g. building automation systems, information monitoring and diagnostic systems, energy information systems). All of these technologies aim to efficiently manage building energy use. EMIS can report and analyze whole-building energy use (e.g. water or electricity), system-level energy use (e.g. just HVAC), or offer a combination of the two.

Despite the demonstration of benefits from MBCx in the 1990s and the beginning of a paradigm shift from retro-commissioning to MBCx in the early 2000s (Meiman et al. 2012), the process remains under-utilized (Granderson and Lin 2016b). This could be because there are still variables acting as barriers to MBCx and supporting technologies like EMIS (King and Perry 2017), confusion about the process, and skepticism towards its benefits (Anderson et al. 2007).

This research aims to make MBCx more transparent by creating a framework of enablers and barriers to its use, based on the synthesis of experiences from organizations implementing EMIS and MBCx. Frameworks can serve as a guide for a specific outcome by organizing interlinked concepts. The framework contains variables that emerge from qualitative data, organized by phases of the MBCx process, and will point out those that are commonly experienced as barriers or enablers to the process. The framework can act as a guide to organizations implementing MBCx by making variables that impact the process more evident; it also suggests further empirical research to determine the relationship between these variables and energy saving outcomes.

The overarching goal of this research is to facilitate otherwise untapped potential for site energy savings by creating a tool for building owners practicing MBCx. This research is intended to benefit commercial building stakeholders such as building owners, facility managers, building engineers, and energy managers involved in the MBCx process, as well as researchers interested in targeting understudied areas of MBCx.

2. Background

Background information relevant to this work includes the relationship between MBCx and information systems, definition of the MBCx process, and examples of variables, or factors impacting the successful implementation of MBCx.

2.1 MBCx relationship to information systems

More than five decades of research in information systems have led to advances in disciplines such as management (Robey 1979), healthcare (Haux 2006), and manufacturing (Coronado M et al. 2002). In general, information systems (IS) are defined as networks, software, and hardware that work together to acquire, store, and manage data (Lucey 2005). The utilization of an EMIS, (see phase two of the MBCx process, in Section 2.2) also requires networks, software, and hardware and could be considered a subset of an IS. Petter, DeLone, and McLean (Petter et al. 2013) defined an IS framework that contains variables that "cause" or at least influence IS success. This framework helped create a better understanding of the IS process and is a starting point for researchers to measure the interactions and outcomes of these variables. Petter, DeLone, and McLean (Petter et al. 2013) defined IS variables based on a synthesis of over 140 studies, then assessed whether these variables, based on literature, have an impact on success outcomes like system use, system quality, user satisfaction, and net benefits. For example, the IS framework identified the variable "user involvement" defined as "the degree to which users participate and are involved in the IS development and implementation process" (Petter et al. 2013). User involvement was then found to have conflicting impacts on the use of the IS and the authors suggested further study (Petter et al. 2013). A similar framework to Petter, DeLone, and McLean's framework, specific to MBCx and developed in this work, can create a more holistic understanding of MBCx and lay the groundwork for comparable empirical studies.

2.2 MBCx process

Analogous to the traditional existing building commissioning processes, the overall MBCx process includes a planning phase, and an implementation phase (Friedman et al. 2011). However, to accommodate the use of IS, it also includes a phase for EMIS configuration. Details of the specific steps within each phase are listed in Table 1, as described in Granderson et al. (Kramer et al. 2017).

The outcome of the research presented in this paper is a framework of variables that influence the MBCx process; the framework is aligned with these phases (see Table 1), and can support organizations in implementing the process. However, since, the variables within the framework may be relevant at multiple points in the MBCx process, the specific phase referenced may serve more as a general roadmap than a definitive attribution.

Table 1. Three phases of the MBCx process

MBCx Planning Phase
1.1 Collect building documentation and create/update current facility requirements (CFR)
1.2 Define high priority systems for performance monitoring
1.3 Create a Monitoring Action Plan (MAP)
1.4 Specify or enhance an Energy Management and Information System (EMIS)
1.5 Create Training Plan
EMIS Configuration Phase
2.1 Define data configuration requirements
2.2 Calibrate critical sensors
2.3 Perform EMIS data quality checks
2.4 Create an EMIS user interface
2.5 Configure the fault detection and diagnostics (FDD)
2.6 Configure energy savings and anomaly tracking
MBCx Implementation Phase
3.1 Identify issues and opportunities using EMIS and Monitoring Action Plan
3.2 Investigate root cause for prioritized issues
3.3 Identify and implement corrective actions, and update facility documentation
3.4 Verify performance improvement
3.5 Implement reporting, documentation, and training

2.3 Examples of variables impacting MBCx

Previous case studies describe some variables (Granderson et al. 2011a; Granderson and Lin 2016b; Motegi et al. 2003; Narayanan et al. 2010; Webster 2005) that act as barriers, impeding the process, or enablers, supporting the institutionalization of EMIS and/or MBCx, and energy saving goals. These variables can be inherent to the MBCx process, but cause unexpected challenges or barriers. For example, the University of California, Merced (UC Merced), adopted an MBCx process and reported that one of the biggest issues was data quality (Granderson et al. 2011a). Although the performance of data quality checks is a step within the MBCx process, organizations might not know how often this actually impedes the process or that this can lead to issues like false positive alarms that cause cascading alert notifications during the implementation phase.

On the other hand, these variables may not necessarily be defined in the general MBCx process, making it difficult for organizations to anticipate their influence. Using the case of UC Merced again, network and connectivity problems led to false alarms that then required "significant resources" to validate the data (Granderson et al. 2011a). Multiple case studies highlight the use of consulting and advisory services as being valuable to MBCx implementation, but this is not clearly defined within the MBCx process and organizations could benefit from learning about the experience of others. For instance, when using outside consultants to configure EMIS, a lack of documentation and training for staff responsible for continued management of the system can lead to improper ongoing use of EMIS (Henderson and Waltner 2013; Smothers and Kinney 2002).

In addition, there are variables described in case studies that can enable energy savings, that are not defined in the MBCx process. For example, one case reports the organization leveraged their EMIS through an energy reduction campaign focused on engaging employees with the building's energy use (Owen et al. 2010). The case highlighted the impact of empowering "energy champions" in supporting others to practice energy-saving behaviors (Owen et al. 2010). EMIS data has also been used to design programs that create a sense of competition between occupants, retail chains, and even communities leading to energy savings (Kramer 2014).

Although these cases are a rich data source, organizations interested in MBCx could benefit from a framework classifying variables, such as these, that act as either barriers or enablers to the process. A framework provides a more holistic perspective than a case study, with context of other variables and their connections to each phase.

3. Research Questions

By using qualitative data from over 40 organizations implementing MBCx and using EMIS for continuous data monitoring and analysis, this research aims to answer the following questions:

(1) What variables emerge from the MBCx process?
(2) At what phase do these variables occur within the MBCx process?
(3) Which of these variables are described as barriers and which are described as enablers?

The qualitative data encompasses a wide range of organizations (in size and type) and multiple EMIS types. The data was coded to determine the emergent variables impacting MBCx and then organized by MBCx process phase to create a MBCx framework. The hypothesis is that variables will emerge as barriers or enablers that are not necessarily defined in the MBCx process. Of those variables, the expectation is to find the majority to be barriers to the process due to the nature of qualitative questions (see Table 2), but we expect that some enablers will emerge as well. It is also expected that some variables will have conflicting results, being barriers to some and enablers to others. These variables are highlighted in the results. Finally, gaps in MBCx knowledge are underscored to encourage further empirical study and outlined in the discussion and conclusion.

4. Methods

This section details the research population, the qualitative data set, and data coding methods used to identify variables and develop the MBCx framework. The coding of data was performed by multiple researchers to ensure internal validity and inter-rater reliability.

4.1 Research population

The population analyzed in this paper came from organizations participating in the Smart Energy Analytics Campaign (Campaign) led by the U.S. Department of Energy under the Better Buildings Alliance. The Campaign is organized by Lawrence Berkeley National Lab (LBNL) ("About the Smart Energy Analytics Campaign" 2017). The goal of the Campaign is to encourage organizations to use EMIS technology to identify energy saving opportunities for their buildings through the practice of MBCx. Organization types involved in the Campaign include higher education (31%), office (36%), laboratory (10%), hospital (10%), retail (5%), grocery (3%), healthcare (3%), and hospitality (3%). Organizations voluntarily enrolled in the Campaign and received free technical assistance and resources in exchange for providing LBNL information about their MBCx process and energy savings.

4.2 Qualitative data set

Throughout participation in the Campaign, each organization was interviewed by a researcher from LBNL and completed multiple surveys about their experience. All data used in this study was stripped of identifying information prior to analysis for the purpose of developing the framework. The data used for this study is outlined in Table 2. The data was recorded either by an LBNL scientist or via self-report from the organization through online surveys, as noted in the reporting method column of Table 2. The specific questions are also detailed in Table 2. The questions chosen from the Campaign for this research were all open-ended and required the organization to reflect on their experience with MBCx. This allowed for the analysis of a rich set of information that could not be gathered from strictly numerical data or responses from closed questions. The number of responses from organizations to each question are also outlined in Table 2.

Table 2. Questions from the Smart Energy Analytics Campaign used to develop the framework

Reporting Method	Specific Question	# Reponses
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	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 Development of the MBCx framework

The qualitative data analysis method is similar to a previously developed inductive coding method (Thomas 2006) that has been used in disciplines such as design (Blizzard and Klotz 2012) and healthcare (Blizzard and Klotz 2012; Weiskopf and Weng 2013). There were seven steps involved in analyzing the data. The following subsections explain each of these seven steps.

4.3.1 Qualitative data was broken into elements

All of the qualitative data from the organizations implementing MBCx was downloaded into an excel database. The data was then divided into individual elements. The original wording of the response was maintained but the responses sometimes comprised entire paragraphs. Consequently, those responses were divided into multiple elements. Each element only contained one principal concept. After breaking down the responses, there were a total of 395 elements.

4.3.2 Codebook was developed with two tiers of keywords

Elements were scanned for significant words to create a preliminary codebook by Coder 1, where two tiers of keywords emerged. Tier 1 keywords contained overarching themes such as analysis & reporting. Tier 2 keywords contained detailed codes related to Tier 1. For example, one Tier 2 keyword was *metrics*, and metrics was a subset of the Tier 1 code, *analysis & reporting*. Coders 2 and 3 reviewed the preliminary codebook and made suggestive edits (e.g. combining similar keywords or adding additional keywords).

4.3.3 Elements were coded with the codebook

All elements were then coded with the finalized codebook containing 51 sets of keywords (13 Tier 1 keywords and 51 Tier 2 keywords). Each element had the potential to be assigned up to two sets of keywords. This is because some elements fell into two different categories. For example, the following element "*Doesn't know if work order connection really makes sense because of false alarms that arise from new meter configurations, or controllers that are off line, etc.*" would fall under the keyword sets of, *system for corrective actions – false alarms (system for corrective actions* being the Tier 1 keyword and *false alarms* being the Tier 2 keyword*)*, but also *system for corrective actions – work orders*. Both sets of keywords provide insight into the organizational issue experienced during their MBCx process.

4.3.4 Elements were classified as barrier or enabler

Coder 1 also classified each element as "barrier", "enabler", or "neutral", depending on the connotation of the element and the particular survey or interview question. For example, the following element “*There is no structured engagement or process to manage the EIS*,” was marked as a barrier because it was a response to the question “*What are your biggest challenges in meeting your plans?*” Since there was not a question that would specifically elicit enablers to the MBCx process only elements that specifically point out advantages were marked as enablers. For example, “*They do weekly meetings with each region… attended even by technicians…accountability is established*,” would be marked as an enabler. “*Can import 15-minute data into software*” was marked as neutral because although interval data is important to MBCx, it was simply an attribute of the organization’s metering in response to “*Please give us an overview of your current data collection…*” and not necessarily highlighted as an extremely successful strategy.

4.3.5 Element coding was validated by multiple coders

Portions of the elements were dispersed between three additional coders for review. These coders are experts with graduate degrees, work experience, and numerous publications related to energy systems and engineering sustainability. There were four coders and each element was coded by at least three coders in order to create a consensus and reduce subjectivity. Any discrepancies between coders were discussed and resolved. A few additional keyword codes emerged and were added to the codebook. Coder 1 then went through a third round of coding and updated respective elements with the emergent keyword codes.

The average percent agreement between Coder 1 and Coders 2, 3 and 4 was 92%. This was determined by the sum of discrepancy with the keyword chosen by Coder 1 and the number of times an additional coder suggested another keyword for a particular element. Table 3 contains details on the specific number of discrepancies and additional keywords suggested. Since the coding for this study involved multiple sets of keywords for each element and 51 different codes, the likelihood of agreement by chance was very low. There are multiple measurements for interrater reliability with more than two raters, such as Fleiss’s kappa, but a simple comparison between coders was chosen because the aforementioned ratings are intended for observational studies (Hallgren 2012).

Table 3. Percent agreement for data coding

In Comparison to Coder 1					
Coder #	**# Elements**	**Discrepancies**	**Additional keyword**	**Total Changes**	**% Agreement**
2	263	5	23	28	89%
3	265	3	5	8	97%
4	262	8	19	27	90%
				Average	**92%**

4.3.6 Elements with the same keywords synthesized into variables

Elements with the same set of keywords were then synthesized to define variables impacting the MBCx process. Essentially, Tier 1 keywords that emerged from the qualitative data coding are now the categories and Tier 2 keywords are now the names of the variables in the framework. For example, the elements *"Challenges in moving too much data, hitting the sweet spot of getting enough info for action*" and *"Dealing with massive amounts of data, but not getting value out of the data. Run out of space for storing trend data, so have to dump it*," both had the keyword set of data – overload. These elements, among others with the same keyword set, were synthesized into the variable definition for data – overload defined as: *"Too much data imported into EMIS. Can lead to challenges in determining amount of data that is useful, mining data, determining how to create value or metrics, managing volume of data, and managing storage space for volume of data."*

Synthesis also involved analyzing the frequency the variable was encountered as a barrier or enabler to measure the impact of variables on the MBCx process.

4.3.7 Variables were categorized by MBCx phase to create the framework

Variables were then categorized by MBCx phase to create the framework. The MBCx phases used were those defined in Table 1. Similar to the original coding phase, three different coders then categorized each variable by the respective MBCx phase using the documented description of what each phase entails. Coder 1 reviewed all three coding arrangements and noted discrepancies. To reduce subjectivity, discrepancies were then discussed and the categorization of variables into the respective MBCx phase was finalized. Finally, a framework was created which contained a category for each major MBCx phase with the respective variables (with the frequency each variable was encountered as a barrier or enabler). The framework is explained in detail in the results section.

5. Results

The MBCx framework that emerged from the qualitative data is comprised of 51 variables that fall within 13 different categories and can be found in the appendix, Table A. Within the variable definitions, there are examples of strategies used in practice related to the variable and also examples from the data of how the variable can act as a barrier or lead to challenges for organizations during the MBCx process. The variables are organized by the three phases of the MBCx process: MBCx Planning Phase, EMIS Configuration Phase, and the MBCx Implementation Phase. Table A table also lists the frequency at which each variable occurred, whether it was classified as a barrier or enabler, and the percent of occurrences in which it was classified as a barrier. The intent of the MBCx framework is for organizations using MBCx to learn from and anticipate the barriers and enablers experienced by other organizations in practice. However, the MBCx framework does not necessarily contain all of the barriers and enablers an organization might face during the MBCx process.

Variables in the framework range from overt to unexpected, based on the definition of MBCx. For example, *measurement and verification* is defined in the MBCx Implementation phase as it is a common method used to quantify savings, so, the emergence of this variable is not surprising. But *business case* - *incentives*, defined as "financial rebates for energy savings" is a variable that organizations might not be aware of by simply understanding the general MBCx process. The category with the most variables (20%) is *analysis & reporting* (see Table 6). *Analysis & reporting* is a single category because these actions often overlap with each other; any analysis carried out is often reported in some way. Granderson et al. (Kramer et al. 2017) define the *Monitoring Action Plan (MAP*) is an essential document for MBCx, which outlines the systems monitored and key analytics and metrics available through the EMIS and is the category with the second most variables (12%). The categories *RFP* and *occupant* both only have one variable because the variables, *occupant* - *engagement* and *RFP* - *developing specifications*, did not naturally fall within any of the other categories. The phases within the MBCx process had 27% (MBCx Planning Phase), 25% (EMIS Configuration Phase), and 47% (MBCx Implementation Phase) of the variables (see Table 7).

The following seven variables were classified as a barrier 100% of the time. That is, if the variable was encountered by the organization, it was always related to a problem:

> *data – naming conventions; data – overload; MAP – maintain; metering – general; staff – energy manager/champion; staff – time; and, system for corrective actions – false positives*.

Organizations expressed the need for an energy manager or champion (related to the variable *staff – energy manager/champion*) devoted to overseeing the MBCx process, but many times existing staff did not have the capacity for new responsibilities and organizations experienced difficulties making the business case for a new hire.

The average frequency a variable was classified as a barrier was 5.25. There were 17 variables that were above average barriers, meaning they were common for the data set, occurring 6 times or more. Those variables are listed in Table 4, organized by MBCx phase and then in descending order by "# Times Classified as Barrier". *Data – configuration* was the top barrier found from the data set occurring 20 times. The high frequency of this variable underscores the difficulty when configuring or integrating data into EMIS. The discussion section offers rationale about why these barriers exist and some are so prevalent.

Table 4. Variables classified as barriers 6 times or more

MBCx Phase	Category	Variable	# Times Variable Occurred	# Times Classified as Barrier	# Times Classified as Enabler	% Variable Classified as Barrier
MBCx Planning Phase	EMIS	Developing Specifications	20	14	2	70%
	Staff	Training/Skills	15	10	0	67%
	Business Case	Budget for Investment	12	9	0	75%
	RFP	Developing Specifications	12	8	0	67%
	Business Case	Management Support/Funding	9	7	2	78%
	MAP	Strategies	42	6	1	14%
EMIS Configuration Phase	Data	Configuration	22	20	0	91%
	IT	Data Architecture	21	14	0	67%
	FDD	Strategies	12	11	1	92%
	Data	Overload	9	9	0	100%
	Data	Quality	10	9	0	90%
	FDD	Configuration	23	8	0	35%
MBCx Implementation Phase	Analysis & Reporting	Measurement and Verification	22	16	0	73%
	Staff	Time	12	12	0	100%
	Staff	Acceptance	12	9	1	75%
	Analysis & Reporting	Metrics	15	7	0	47%
	Business Case	Payback/ROI	14	7	3	50%

Very few variables were found to be enablers, with the highest occurrence being *business case – payback/ROI* classified as an enabler three times. This is not surprising, due to the nature of the questions analyzed (see Table 2), which implicitly solicit more barriers than enablers, as noted in section 5.1 Limitations. Interestingly, there were 12 variables, including *business case – payback/ROI*, with conflicting results. Meaning, these variables were encountered as a barrier to one organization and an enabler to another. Those variables are listed in Table 5 organized by MBCx Phase. For example, *business case – payback/ROI* was considered a barrier seven times and an enabler three times. One organization had difficulty making the business case for the initial investment for MBCx due to lack of cost information, while another was able to justify large investments with documented savings of previously implemented measures.

Table 5. Variables classified as a barrier and enabler

MBCx Phase	**Category**	**Variable**	**# Times Variable Occurred**	**# Times Classified as Barrier**	**# Times Classified as Enabler**	**% Variable Classified as Barrier**
MBCx Planning Phase	Business Case	Management Support/Funding	9	7	2	78%
MBCx Planning Phase	EMIS	Developing Specifications	20	14	2	70%
MBCx Planning Phase	MAP	Energy Management Team	27	5	1	19%
MBCx Planning Phase	MAP	Strategies	42	6	1	14%
EMIS Configuration Phase	FDD	Strategies	12	11	1	92%
MBCx Implementation Phase	Analysis & Reporting	Strategies	7	2	2	29%
MBCx Implementation Phase	Business Case	Payback/ROI	14	7	3	50%
MBCx Implementation Phase	Business Case	Strategies	5	2	1	40%
MBCx Implementation Phase	FDD	Fault Identification	18	5	1	28%
MBCx Implementation Phase	Staff	Acceptance	12	9	1	75%
MBCx Implementation Phase	System for Corrective Actions	Strategies	11	2	2	18%
MBCx Implementation Phase	Third Party Support	Service Providers	19	5	1	26%

Table 6 shows the breakdown of the percent of variables and barriers in each category. The category with the most barriers is data, with 16% and it only had 8% of the variables. Staff and analysis & reporting both had 14% of the barriers. The phases of the MBCx process shared the barriers almost evenly with MBCx Planning Phase having 30% of the barriers (27% of total variables), EMIS Configuration Phase with 36% (27% of total variables), and MBCx Implementation Phase with 34% (45% of total variables).

Table 6. Percent of variables and barriers in each category

Category	% Variables	% Barriers
Analysis & Reporting	20%	14%
MAP	12%	9%
Business Case	10%	9%
Staff	10%	14%
System for Corrective Actions	10%	5%
Data	8%	16%
Metering	8%	4%
FDD	6%	9%
Third Party Support	6%	2%
EMIS	4%	7%
IT	4%	7%
Occupant	2%	1%
RFP	2%	3%

5.1 Limitations

There are several limitations to this research. First, the organizations involved in the Smart Energy Analytics Campaign were self-selected, comprising participants in a voluntary initiative. These organizations also represent relatively early adopters of MBCx within the commercial buildings sector. Therefore, this sample may be generally representative organizations interested in practicing MBCx. Second, it is important to note that recall bias can impact the accuracy of the self-reported data during the interviews. This is more relevant to the enablers of the MBCx process, as organizations were specifically reporting issues or barriers in order to receive technical assistance and, as mentioned, the nature of the questions implicitly solicit more barriers than enablers (see Table 2). And, since this data was reviewed post-interview, the context of some statements was difficult to determine, leading to many elements classified as neutral. Third, the qualitative data coding was initially somewhat subjective. However, this research aimed to reduce this subjectivity by using multiple subject matter experts as coders to confer on discrepancies.

6. Discussion

The EMIS Configuration Phase contained 27% of the variables, but contained 36% of the barriers. This suggests that an organization is likely to run into barriers during the EMIS Configuration Phase. The MBCx planning phase has the same percent of variables, 27%, and just 30% of the barriers. A more thorough analysis of the individual barriers themselves can lead to a better understanding of the distribution of barriers; whether organizations actually experience fewer issues during planning or if poor planning does lead to more issues later in the process.

Although some of the variables had a low number of occurrences, this could be because some organizations were earlier in the process. The variables *MAP – maintain energy savings* and *system for corrective actions – false positives* only occurred twice, but were classified as a barrier both times. Since these variables are likely to impact the MBCx Implementation Phase, they could be expected to occur for other organizations as they reach the later phases of the process.

Some variables experienced as barriers were unsurprising and this emphasizes the need for more research on enablers to overcome them. The highest occurring barrier was *data – configuration*, which is a crucial step during the EMIS Configuration Phase. Data configuration commonly slows the MBCx process, as supported by this research and previous case studies that described the same problem. The framework lists some of the causes of this barrier, like limited data due to old BAS, or issues due to different vendors or controls companies in hopes that organizations could then anticipate these issues and make sure to have the right people at the table to resolve them.

The variable *staff – acceptance*, classified as a barrier nine times, has been an issue since the advent of IS technologies such as fault detection and diagnostics tools. It is normal for organizations to experience difficulties with institutionalizing MBCx due to staff being hesitant to accept the new process and technologies. Nevertheless, organizations new to MBCx could benefit from having this pointed out in the framework. By being aware of this potential barrier, time can be set aside to do things like, point out the benefits for building operators, or give examples of problems discovered by other organizations using MBCx that may otherwise go unnoticed and could help dispel some of the staff members' hesitation. Organizations could also experiment with extrinsic incentives to encourage staff to practice MBCx. These are suggested enablers that could be studied in detail in future research.

The variable *analysis & reporting – measurement & verification* (M&V) was the second highest occurring barrier. There are many ways to satisfy the "Verify performance improvement" step of the MBCx Implementation Phase, including operational checks, energy consumption tracking, and tracking of other key performance indicators and performance metrics. Many organizations, however, desire to assess savings through a formalized M&V approach. In this research, organizations reported challenges using their EMIS embedding and automating M&V capabilities, often not knowing where to start. This illustrates that while M&V is an emerging and potentially powerful capability in many EMIS offerings, users are still acquiring the practical experience required to successfully utilize it.

Variables that were classified as variables 100% of the time also warrant further research. *Staff – time* and *data – overload* both lead to the struggle in finding a balance for getting the most value out of MBCx. The MBCx process does not define how much data or time leads to the most impact on energy savings.

As expected, this research does not provide in-depth insight on the enablers to MBCx, yet it is worth considering variables that had conflicting results. This demonstrates that while there are variables that commonly cause barriers to the process, when anticipated proactively, organizations can leverage these to enable the process. Moreover, variables found to be barriers 100% of the time could potentially become enablers as the state of practice of MBCx evolves. For example, currently, *staff – energy manager/champion* was only found to be a barrier. This could be because the current norm is not to have a staff member solely responsible to manage energy use. If an organization is able to define this new role, it could become an enabler to the process, but when an organization was lacking this role, it was a barrier.

Variables found to be completely neutral, neither marked as an enabler or barrier, might emerge differently if studied more specifically. For example, the variable *business case – incentives* was neutral, but intuitively, an incentive to something would be expected to be an enabler.

Practitioners implementing MBCx should take away that there is no single remedy to reduce barriers. Barriers occur throughout the process and can be related to tools to support the process, and the staff, leading to interconnected issues between technology and human resources. However, focusing on variables within several key categories can help. For example, analysis & reporting, staff, and data compose 44% of reported barriers. Getting these variables correctly aligned removes about half of the reported barriers. Going further, making the business case, properly setting up the monitoring action plan (MAP), and fault detection and diagnostics (FDD) can reduce the reported barriers by over 70%.

7. Conclusion

MBCx is becoming a more common method to discover and maintain energy savings in buildings, but barriers to the process still exist, as validated by this research. By developing a MBCx framework this research has synthesized the experiences of over 40 organizations to define emergent variables and begin defining commonly experienced barriers and enablers. The framework reveals that variables impacting the MBCx process can act as barriers to one organization and enablers to another, depending on the circumstances within the organization. Although some variables in this research occurred exclusively as barriers, those with conflicting results reveal that this exclusivity is not infallible. This MBCx framework can help communicate these variables, and by simply increasing awareness, organizations will be able to better understand and plan for them.

Future research can expand this framework and add to the understanding of the MBCx process. Although best practices and guidebooks exist for MBCx, a large data set that explicitly focuses on enablers to MBCx for practicing organizations could help validate these existing resources. More empirical studies can investigate the relationships between specific variables. For example, the highest occurring barrier of *data - configuration* (and associated data quality problems) could lead to the question: What changes to the data configuration process would result in more efficient and consistent EMIS implementation, with higher data quality? For variables that are expected, like *staff – acceptance*, researchers could see if there are interacting affects between variables such as: Does third party support slow or advance staff acceptance of MBCx?

There is a strong need to elicit and validate common enablers to the MBCx process. Future research can also pull from existing information systems research to help design these studies and define variables to measure the success of MBCx.

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Journal Paper:

Barriers to Monitoring-Based Commissioning due to Cognitive Biases

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Authors:

Nora Harris [a, *],

Tripp Shealy [a]

Kristen Parrish [b]

a. Charles Edward Via, Jr., Department of Civil and Environmental Engineering, Virginia Tech, 200 Patton Hall, Blacksburg, VA 24061, USA
b. School of Sustainable Engineering and the Built Environment, Arizona State University, 660 S College Ave, Tempe, AZ 85287, USA

*Correspondence: neharris@vt.edu

Abstract

Although monitoring-based commissioning (MBCx) can reduce energy use in buildings 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 also contribute to issues implementing and using MBCx. More specifically, 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 due to the following cognitive biases: 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 that can impact their processes and make more informed decisions. Researchers can use these results to empirically test specific decision interventions to help overcome the cognitive biases, and facilitate more energy efficient decisions.

1.0 Introduction

Existing commercial buildings 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 et al. 2006; Kramer et al. 2017; Mills and Mathew 2014). The MBCx process has been shown to reduce up to 20% of a building's energy use (Granderson and Lin 2016). However, an energy efficiency gap 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 et al. 2011a; Granderson and Lin 2016; Mills and Mathew 2014; Motegi et al. 2003).

Behavioral decision science research suggests that a portion of this energy efficiency gap, between the energy saving potential of processes like MBCx and observed savings, can be attributed to irrationalities in human decision-making (Wilson and Dowlatabadi 2007).

This research aims to better understand organizational decision making that often slows or halts the implementation of MBCx, using a behavioral decision science lens. Behavioral decision science concepts, specifically cognitive biases, can help explain the irrationalities or errors in judgment that led to such energy waste in buildings. Behavioral decision science also provides proven decision interventions to overcome these biases, providing potential to increase the use of MBCx and improve building energy efficiency. The goal is to provide building stakeholders such as building owners, building engineers, or facility mangers with knowledge of specific cognitive biases that could be impacting their decisions to help them be more equipped to overcome these biases and maximize utility. For the purpose of this study, maximizing utility corresponds to maximizing energy efficiency. Behavioral decision science and energy efficiency researchers can use this paper to begin developing empirical studies to test specific decision interventions for the cognitive biases identified in the results of this study.

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

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. (In Review) 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 and 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, UC 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. 2011b).

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. 2011b). 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 the configuration of the EMIS, including meter installation, web interface development, and HVAC monitoring and alert services (Henderson and 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 wouldn't building engineers use the EMIS that was intended to provide data for more informed decisions?

Behavioral decision science can provide insight into the deeper meaning behind these issues in the decision-making process, which may be inhibiting more pervasive uptake of MBCx processes in commercial building energy management. This paper examines the barriers to MBCx through a behavioral decision science lens to better understand the origins of these seemingly irrational decisions, specifically searching for evidence of cognitive biases, as described in the next section.

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 economics research demonstrates that individuals routinely make irrational decisions, especially when faced with uncertainties, leading to outcomes that do not maximize utility (Camerer et al. 2011; Khaneman and 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 and 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.

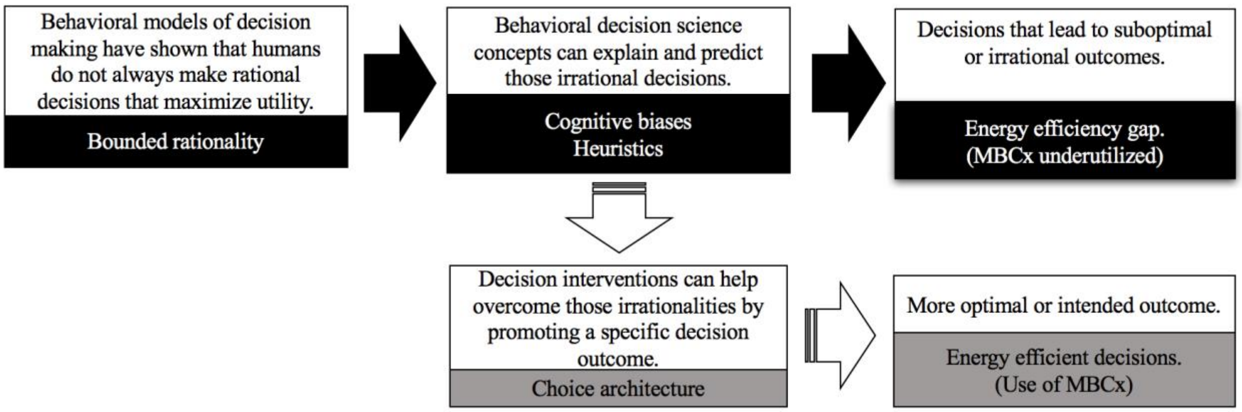

Figure 1. Applications of Behavioral Decision Science Can Lead to More Optimal and Energy Efficient Decisions

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 with the goal of this paper to determine if they are similarly impacting MBCx. The selected cognitive biases include: choice overload, information overload, risk aversion, temporal discounting, social norms, professional bias, and status quo bias. These particular biases are highlighted here, as they are those that emerged from the research findings (see Research methodology).

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 and Lepper 2000) or not making a choice at all (Dhar 1997). Muthulingam et al. (2013) found that adding more options to a list of energy saving recommendations does not necessarily impact the number of recommendations pursued, but found a modest negative impact on the overall energy savings.

Information overload

Similar to choice overload, information overload can negatively impact decision-making (Edmunds and 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 and 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 et al. 2013; Dalén and Krämer 2017). 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.

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 and Tversky 1979; Tversky and Kahneman 1992). Risk aversion can predict how homeowners selling in a down market may insist on a higher asking price (Genesove and 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 and Ariely 2000; Cummings et al. 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 (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.

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 (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; Delgado 2017). Bounded rationality can explain this shortsightedness in management decisions about energy-efficiency (DeCanio 1993).

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).

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 and Claridge 1993; Woradechjumroen et al. 2014).

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 and 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 and 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 and Katsikopoulos 2008).

3.0 Research objective

The objective of this research was to identify whether, and which, cognitive biases impede the MBCx process throughout its planning, configuration, implementation, and continued use. By identifying which cognitive biases exist, practitioners can become more aware of their own, and their colleagues', barriers to 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 the long-term benefits 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 encourage interdisciplinary research to find solutions to interlinked 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 an LBNL researcher during phone interviews with participants. Surveys were completed via self-report by participants through a web-based form instrument. 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 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 7. 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?*" 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.

4.4 Specific cognitive biases selected

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 each with 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). 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 to the list for a total of 7 cognitive bias codes. 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. Coding examples and rationale are listed in Table 2.

Table 8. 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

4.5 Element coding was validated by two additional coders

The three coders coded all 185 elements with the finalized list of cognitive biases. 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.

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. In Review)

Table 9. 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 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. Risk aversion is also related to temporal discounting (occurring 3 times), where participants had difficulty gaining buy-in due to shortsightedness demonstrated by management with simple payback thresholds or ROIs of 2 years or less.

The second highest barrier, social norms, occurred 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 the social norms related to MBCx are perceived as 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, occupants would visually see how their behavior is having an impact and lead to a sense of responsibility.

Similarly, professional bias (occurring 4 times), was exhibited when a participant reported that some of their specific team members, such as operations staff, resisted buying in to the use of EMIS as it was not conventionally expected as a part of their role. With status quo bias (occurring 8 times), participants were failing to get the full value out of their EMIS, by simply relying on existing process, 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. Social norms, professional bias, and status quo bias are all related to the resistance of change.

Choice overload, occurring 10 times, 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 (occurring 8 times) was always related to the data made available by EMIS. Participants struggled to manage the volume of data and get value out of the information, leading to issues such as difficulty "prioritizing faults" that were identified by EMIS.

5.1 Limitations

The organizations that elected to participate in the Smart Energy Analytics Campaign represent relatively early adopters of MBCx within the commercial buildings sector. Therefore, this sample may be generally representative organizations interested in practicing MBCx. 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".

The next section will make 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 that was analyzed are due to cognitive bias. 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 and 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 top cognitive bias, 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 and 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 the energy bill, 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% (Houde and Todd 2011).

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 and Kavazovic 2010), and telling residents that their neighbors were conserving energy (Nolan et al. 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 models. 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 et al. 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 using MBCx. The Smart Energy Analytics campaign encourages this through peer-to-peer exchange (“About the Smart Energy Analytics Campaign” 2017).

Choice overload, experienced by organizations when choosing an energy management information system (EMIS), can be reduced by “collaborative filtering” (Thaler and Sunstein 2008). Collaborative filtering takes advantage of choices made by individuals with similar interests (Thaler and 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.

These are just some examples of decision interventions, more specifically choice architecture techniques, 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. Not only that, but future research can 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. These interventions can be empirically tested by researchers, but can be implemented by the 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 cognitive biases, can prevent MBCx from being pursued altogether.

7.0 Conclusion

This paper has extended research on the connections between behavioral models of decision making, choice architecture, and energy efficiency decisions to include decisions specifically related to monitoring-based commissioning (MBCx). This paper identifies specific cognitive biases in MBCx. The results can be used by practitioners, such as facility managers, building engineers, or energy managers, to become more aware of the negative impact cognitive biases can have on decisions for energy efficiency. Practitioners can then incorporate choice architecture tools when making decisions like how to present the business case or determining the proper energy management information system (EMIS).

Researchers can use these results as justification for researching specific cognitive biases and decision interventions. For example, risk aversion should be a focus in MBCx research as it was the highest occurring barrier for organizations. Development of choice architecture tools to help overcome risk aversion is a logical priority for making the business case for MBCx. Ultimately, this research intends to promote awareness of cognitive biases in MBCx to lead to more interdisciplinary research to define and empirically test decision interventions and choice architecture tools to overcome these biases, resulting in more energy efficient decisions.

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CONCLUSION

This manuscript offers insight on the general barriers to monitoring-based commissioning (MBCx) in chapter 1, and insight on decision-making barriers due to cognitive biases in chapter two. Chapter 1 validated barriers that have already been described in previous case studies with a large data set, highlighting those that are more commonly experienced, like data configuration issues. Chapter 1 resulted in a framework which can be used by practitioners to better understand experiences of other organizations during the MBCx process. The framework can be used by researchers to pinpoint future research questions, such as variables in the framework with conflicting results.

Chapter 2 describes evidence of cognitive biases in previous research on energy efficiency decisions as a justification for analyzing decision-making within the MBCx process for cognitive biases. Within the qualitative data from over 40 organizations using MBCx, chapter 2 resulted in evidence of multiple cognitive biases, with risk aversion being the most common. This suggests that irrationalities in human decision making are exhibited in the MBCx process in the form of cognitive biases. These cognitive biases can impede MBCx resulting in less energy efficient decisions. Choice architecture is offered as a solution to help reduce the impacts of these cognitive biases.

Both chapters of this manuscript reveal the need for more research with a large data set to validate common enablers, or ways to overcome those barriers. Chapter two suggests specific enablers, in the form of choice architecture, that could be used by organizations to help reduce cognitive bias, but should also be tested empirically by researchers. This research aimed to make the MBCx process more transparent to give organizations a better understanding of the potential barriers in hopes that they could better prepare for and therefore be more willing to implement MBCx to reduce their building energy use

APPENDICES

Table A. MBCx framework

MBCx Phase	Category	Variable	Variable Description	# Times Variable Occurred	# Times Barrier	# Times Enabler	% Barrier
MBCx Planning Phase	Business Case	Budget for Investment	The budget or funding for EMIS related investments such as hardware (e.g. submeters); ongoing software cost; or ECMs. Can lead to challenges demonstrating the value of EMIS to secure budget.	12	9	0	75%
MBCx Planning Phase	Business Case	Management Support/Funding	Management support and buy-in to EMIS. Strategies include: creative ways of presenting EMIS benefits to gain management support (E.g. pitch as maintenance savings benefit); using pilot project savings to gain management support/funding. Can lead to challenges with payback thresholds set by management; risk aversion of management; management requesting M&V of projects.	9	7	2	78%
MBCx Planning Phase	EMIS	Developing Specifications	Decisions during EMIS selection and specific features needed such as the reporting method and capability of EMIS (e.g. dashboard; frequency of EMIS data update). Can lead to challenges finding EMIS with flexibility and specific features; developing RFP; determining if it is best to own EMIS or use the software as a service model.	20	14	2	70%

MBCx Planning Phase	Monitoring Action Plan	Commissioning	Types of commissioning such as connected commissioning or retro commissioning. Strategies include: programs to continuously commission or MBCx; periodic retro-commissioning; using third party service providers for retro-commissioning; peer groups for continuous commissioning; connected commissioning. Organizations often interested in peer groups to learn more about strategies.	7	3	0	43%
MBCx Planning Phase	Monitoring Action Plan	Energy Management Team	Energy management team/roles. Strategies include: different reports based on role in organization; necessity of collaboration between different roles. Examples of different roles: Finance person within energy group (document ROI); Field engineers (monitoring EMIS daily); Managers (receive reports); Controls engineer; Energy engineer; Data scientist (to program FDD); Property manager (receive reports); Facility team or Commissioning staff (manage system for corrective actions); Director of Operations (receive reports); Consultant team (manages EMIS). Can lead to challenges when existing organization has staff constraints or does not have team members with the expertise to carry out monitoring action plan.	27	5	1	19%
MBCx Planning Phase	Monitoring Action Plan	Scaling	Strategies for scaling EMIS or MBCx to multiple buildings within a portfolio. Strategies include: Central database for all facilities; EMIS standardized across portfolio after a pilot run; Support from third party to support scaling EMIS to portfolio. Can lead to challenges with deploying EMIS in multiple buildings within a portfolio.	9	4	0	44%

MBCx Planning Phase	Monitoring Action Plan	Strategies	Tools or strategies defined in the Monitoring Action Plan (MAP) used to identify issues and energy conservation measures. Strategies include: BAS trending for MBCx; FDD alarms monitored consistently (daily; weekly; etc.); checking for overrides on temperature settings; eliminating off-hours energy use (e.g. equipment running overnight); using historical trends to develop strategies; re-commissioning of systems; upgrades to old hardware and software; new installs implemented by controls and mechanical contractors; daily systems monitoring; improvements to set points; schedules; and sequences; development of process standards; alarms and notifications for demand thresholds; focus on major equipment due to time constraints; system for occupants to report hot/cold to optimize buildings; real-time data to allow for proactive responses; identification and understanding of peak demand; review of interval data. Can lead to challenges if there is not a structured process to use EMIS properly; manual FDD or other analytics; and difficulty deciding between in-house or third party commissioning.	42	6	1	14%
MBCx Planning Phase	Metering	Interval	The necessary interval data from meters and whether it is real time vs. delayed. Interval data may be used only on specific buildings or equipment. Upgrades to smart meters may be necessary to obtain instantaneous interval data. Can lead to challenges if there is no availability of interval data; or utility only providing day-behind interval data.	15	2	0	13%
MBCx Planning Phase	Metering	Submetering	Submetering used for end-use (e.g. mechanical equipment; data centers); to break out buildings from a main meter. Can lead to challenges configuring submeters; determining how many submeters are necessary for information without a high cost.	8	3	0	38%

MBCx Planning Phase	Metering	Systems or Points Metered	Systems metered; monitored; points; etc. Examples of Systems Metered: Building level meters; all utilities; integration of metering data from utility bills (electrical, gas, water bill); central plant; mechanical equipment; terminal equipment; chilled and hot water systems. Can lead to challenges determining proper number of points to meter due to meter cost; determining number of points to bring into EMIS.	27	3	0	11%
MBCx Planning Phase	RFP	Developing Specifications	Development of request for proposal (RFP) for specifications such as: back-end; specific FDD rules; FDD features; EMIS features; EMIS integration with maintenance operations. Can lead to challenges developing RFP to meet needs or understanding proposal submittals.	12	8	0	67%
MBCx Planning Phase	Staff	Energy Manager/ Champion	A staff member exclusively devoted to spearheading the MBCx and use of EMIS. Can lead to challenges for organizations without a full-time energy manager and challenges making the case for a full-time energy manager.	4	4	0	100%
MBCx Planning Phase	Staff	In House Staff	Use of in-house staff (as opposed to third party) for management of EMIS and MBCx. Can lead to lower costs and full benefit of incentives from utility; but also, to challenges such as staff training.	5	2	0	40%
MBCx Planning Phase	Staff	Training/Skills	Skills/Training required to use EMIS functionality; analyze EMIS data; configure and utilize FDD; implement ECMs; develop useful EMIS dashboard and metrics Can lead to challenges when there are staff or time constraints involving any of the required skills or training mentioned above.	15	10	0	67%

EMIS Configuration Phase	Data	Configuration	Configuring or integrating data from hardware into EMIS including BAS points and meters. Can lead to challenges with data integration BAS (specifically old BAS); limited data due to old BAS or other system; data integration from different vendors or controls companies (disparate systems); getting all data into a central location; determining how much data to bring in; difficulty bringing in data due to IT issues.	22	20	0	91%
EMIS Configuration Phase	Data	Naming Conventions	Data naming conventions or tagging protocol. Can lead to challenges developing naming conventions; tagging protocol strategy.	3	3	0	100%
EMIS Configuration Phase	Data	Overload	Too much data imported into EMIS. Can lead to challenges: Determining amount of data that is useful; mining data; determining how to create value or metrics; managing volume of data; managing storage space for volume of data.	9	9	0	100%
EMIS Configuration Phase	Data	Quality	The quality of data streams being imported into EMIS. Can lead to challenges getting accurate data from meters (e.g. meters offline; meter calibration); troubleshooting data losses and inconsistency (technical vs. human error); data errors due to communication problems (e.g. drop-outs; data spikes); data history not being retained.	10	9	0	90%
EMIS Configuration Phase	EMIS	Configuration	Setting up the interface or dashboard of EMIS/EIS or other specifics related to interface and dashboard configuration. Can lead to challenges in configuring dashboard to support needs; creating EMIS dashboard for public; creating a real-time EMIS dashboard.	6	5	0	83%

EMIS Configuration Phase	FDD	Configuration	Methods to set up or manage fault detection and diagnostics (FDD) rules or faults. Strategies include: in-house development of FDD to allow staff to better understand system; third party configuring FDD; use of FDD used to uncover faults and energy and operational savings; standard FDD rules deployed at all buildings within a portfolio; additional FDD alarms added after systems initially optimized; coupling FDD alarms with other strategies to maintain building energy baseline. Can lead to challenges writing FDD rules; testing FDD rules; vendor configuring a limited number of rules; diminishing returns of FDD after initial issues found.	23	8	0	35%
EMIS Configuration Phase	FDD	Strategies	Need for peer support for fault detection and diagnostics (FDD) in hopes to learn FDD strategies from similar organizations implementing FDD. FDD can lead to many challenges (see FDD – Configuration), leading many organizations to seek out peer support.	12	11	0	92%
EMIS Configuration Phase	IT	Data Architecture	Data server (hosting data; on-site or cloud); database management; and the network or protocol for sending data. Connecting to external servers. Can lead to challenges in the creation of a single data warehouse; desire for open communication protocols (vs. proprietary); need for servers dedicated specifically to BAS; loss of data without data repository/backup; integration of data into EMIS (time and effort); data access; coordination with IT team.	21	14	0	67%
EMIS Configuration Phase	IT	Data Security	The security of data being sent from meters and systems to EMIS. Can lead to challenges with IT lockdown of BAS servers; necessity of private networks (vs. public).	5	4	0	80%

EMIS Configuration Phase	Monitoring Action Plan	Building Automation System (BAS; BMS; BMCS; EMS; EMCS)	The integration of BAS data for use with EMIS with the goal of saving energy. Strategies include: BAS data used for FDD; BAS trending for MBCx; reprogramming BAS routines for energy savings; documentation of BAS control sequences for insight on building operation. Can lead to challenges with multiple controls companies for BAS; necessity of central location to view BAS data; BAS data causing network issues; updating of BAS in order to integrate data into EMIS.	12	5	0	42%
EMIS Configuration Phase	Metering	General	General metering concerns such as calibrating and accessing meter data. Can lead to challenges with meters falling out of calibration; accessing meter data (not available through a network and must manually export on site).	3	3	0	100%
EMIS Configuration Phase	Occupant	Engagement	Involvement of occupants in buildings with EMIS. Strategies include: public facing EMIS dashboard with aims to change occupant behavior; dashboard for occupants to report hot and cold; signage to encourage energy saving behavior. Can lead to challenges in developing public-facing dashboards.	7	3	0	43%
EMIS Configuration Phase	Third Party Support	Software Vendors	Use of vendors to set up EMIS; etc. Strategies include: Vendors configuring FDD rules; partnering with vendors to resolve EMIS software issues.	4	0	0	0%
MBCx Implementation Phase	Analysis & Reporting	Baseline	The use of baselining for M&V purposes (meter-level baselines or pre-condition); for the baseline of a key performance indicator to measure deviations over time; for regression analysis; or to understand historical trends. Can lead to challenges developing baseline and incorporating weather normalization.	4	2	0	50%

MBCx Implementation Phase	Analysis & Reporting	Benchmarking/ EUI	Benchmarking or EUI where energy use is compared to other similar buildings for analysis; reporting; or to set energy saving goals. Examples include: comparison of EUI between similar buildings; calculating EUI from utility bill. Can lead to challenges for buildings with unique usage that do not have a direct comparison.	13	1	0	8%
MBCx Implementation Phase	Analysis & Reporting	Demand	Analyzing current demand and developing a strategy for peak load reduction; demand response; etc. and may require submeter. Examples includes: EMIS used for formal and informal demand; determining load on network; demand testing to determine main circuits responsible for load; setting alarms or notifications based on load; using EMIS to determine peak load; regression modeling to predict demand and make control changes; demand controlled ventilation. Can lead to challenges determining demand due to inaccurate meter data; automating demand response	16	3	0	19%
MBCx Implementation Phase	Analysis & Reporting	Frequency	The frequency with which reports are generated using EMIS data and shared with stakeholders or building occupants. Frequency can be weekly; monthly; quarterly; etc. Strategies include: changes in reporting frequency depending on role in organization (E.g. monthly reports to management and daily reports to technicians and energy analysts); team meetings to review reports.	12	0	0	0%

MBCx Implementation Phase	Analysis & Reporting	Heat map	The use of heat maps to find issues and review energy use or check building schedule.	3	0	1	0%
MBCx Implementation Phase	Analysis & Reporting	Manual Methods	Analysis or reporting methods; such as M&V; performed manually. Examples include: spreadsheet analysis; comparing nameplate data to equipment performance; reviewing trends and comparing to actual values. Can lead to challenges due to time constraints and generally the goal is to automate.	7	3	0	43%
MBCx Implementation Phase	Analysis & Reporting	Measurement and Verification	Methods of measurement and verification (M&V) for ECMs; quantification of ECM savings; and proof for rebates and incentives. May require submetering. Can lead to challenges to embed M&V into EMIS and automate M&V.	22	16	0	73%
MBCx Implementation Phase	Analysis & Reporting	Metrics	Specific metrics that are reported to track change of energy use due to the use of MBCx or RCx and to track and set goals for buildings within a portfolio. Specific examples of metrics include: energy use; cost (demand charges; taxes; fees); GHG emissions; EUI; utility bill based metrics; load ratio (high or low). Can lead to challenges analyzing EMIS data; developing KPIs; the creation of different metrics/dashboards for different roles within an organization; transitioning from manual to automatic analysis; and difficultly comparing EUI due to variations in building use.	15	7	0	47%

MBCx Implementation Phase	Analysis & Reporting	Strategies	General analysis or reporting strategies. Examples include: FDD alarms reviewed in reporting meetings; integrating bill processing with EMIS analytics; using analytics to maintain optimal performance; using analytics to prioritize investment in projects. Can lead to challenges with the development of reporting and analytics.	7	2	2	29%
MBCx Implementation Phase	Analysis & Reporting	Weather Normalization	The integration of weather normalization in analysis or reporting. Can lead to challenges with integration of the weather normalization.	4	2	0	50%
MBCx Implementation Phase	Business Case	Incentives	Financial Incentives or rebates for energy savings. Examples include: Energy efficiency incentives from utility company; rebates from utility company; M&V used to verify incentives and gain rebates; rebates/incentives used to fund energy manager position or third party service; payment from utility company to reduce peak load.	6	0	0	0%
MBCx Implementation Phase	Business Case	Payback/ROI	Payback or Return on Investment (ROI) of an energy conservation measure identified by using EMIS or of the EMIS itself. Strategies include: ROI used to prioritize projects; using estimated savings and annual price estimates from vendor to determine payback; pilot projects used to demonstrate payback. Can lead to challenges with a specific payback time required in order to pursue project (e.g. client only interested in 1 year payback); difficulty obtaining cost info necessary to develop ROI numbers; diminishing ROI on FDD software.	14	7	3	50%

MBCx Implementation Phase	Business Case	Strategies	General justification strategies for the business case of EMIS or ECMs identified by using EMIS. Strategies include: justify funding as part of a new construction Cx project; using data visualization to help determine investment strategy; centering business case around pilot building; using benchmarking to make business case; using examples of others' success with EMIS to make business case to management. Can lead to challenges accessing data to develop initial business case.	5	2	1	40%
MBCx Implementation Phase	FDD	Fault Identification	FDD strategies used to identify issues causing faults; and opportunities found for energy conservation measures. FDD may also be integrated with the work order system. Often needed to sustain ECM savings. Strategies include: FDD identifies wasted energy; FDD cross-checks equipment operation to operating hours; FDD identifies low airflow due to failed damper; FDD identifies failed sensors; FDD identifies reheat valves cycling improperly. Can lead to challenges integrating FDD with system for corrective actions or work orders.	18	5	1	28%
MBCx Implementation Phase	Monitoring Action Plan	Maintain	Maintaining savings achieved from MBCx. Can lead to challenges when there is no FDD to maintain savings; due to the human factor of maintaining savings (e.g. needing people to regularly check systems).	2	2	0	100%
MBCx Implementation Phase	Staff	Acceptance	Staff acceptance or buy-in of MBCx and institutionalizing the MBCx process. Can lead to challenges when staff resist accepting EMIS or do not use EMIS; staff manually operating system (e.g. BAS) and overriding EMIS; issues with staff maintaining savings.	12	9	1	75%

MBCx Implementation Phase	Staff	Time	Anything related to staff or person-hours required for analysis; measure implementation; etc. Can lead to challenges due to labor bottlenecks; time to analyze EMIS data to gain insight; time to work with EMIS service providers; time to implement ECMs; time required for root cause analysis of issues.	12	12	0	100%
MBCx Implementation Phase	System for Corrective Actions	False Positives	False alarms from smart alarms or false positives for FDD faults. Can lead to challenges integrating alarms with system for corrective actions. Examples include: alarm when there is no issue; alarm from new meter configuration.	2	2	0	100%
MBCx Implementation Phase	System for Corrective Actions	Measures	Specific issues identified and fixed and ECMs implemented. Examples of Issues Fixed (Also see FDD - Fault Identification): VAV boxes open improperly; Simultaneous heating and cooling; Air handler running at maximum capacity; Overcooling; Simultaneous power-up of equipment; Single set points in BAS (as opposed to having a heating and cooling set point); Reheat valves modulating with parent AHU off; VFDs operating at constant velocity; Broken damper actuator preventing reset strategy. Examples of Measure implemented: Reduce outside air to minimum code requirements; Reduction of exterior lighting; Equipment shutdown sequencing; Schedule changes (e.g. no lighting on weekends and off hours); Zoning to reduce heating and cooling in unused areas; Lighting retrofits; Standardization of heating and cooling set points; Proper air change rates; Optimizing lead/lag control in chilled water and hot water; pump operation; Using occupancy sensors to create AHU schedules; Adding VFDs to hot water pump; Static pressure and temperature resets	22	2	0	9%

MBCx Implementation Phase	System for Corrective Actions	Prioritize	Methods used to prioritize measures; issues; or projects identified using EMIS. Strategies include: Prioritizing FDD faults; prioritizing equipment based on power consumption; prioritizing FDD faults by cost impact; prioritizing buildings within portfolio by benchmarking; prioritizing projects by changes in annual energy use. Can lead to challenges developing prioritization strategy for organization's needs.	8	2	0	25%
MBCx Implementation Phase	System for Corrective Actions	Strategies	General strategies for a system for corrective actions: partnering with vendors to resolve issues; FDD alarms reviewed and assigned to technicians weekly; EMIS enabling quick detection of issues; choosing vendor with ability to integrate into existing maintenance operations. Can lead to challenges finding EMIS that integrates well with current system for corrective action; developing a consistent process for tracking and fixing issues.	11	2	2	18%
MBCx Implementation Phase	System for Corrective Actions	Work Orders	Process for fixing issues or implementing energy conservation measures. Strategies include: Integration of FDD alarms with work order system; manually creating work orders based on FDD alarms; EMIS work orders tracked with general facility management work orders; commissioning agent identifying issues and working with technicians to take corrective actions Can lead to challenges in integrating FDD with work orders due to false alarms; coordination with third parties; tracking alarms from FDD with resolution.	11	4	0	36%

MBCx Implementation Phase	Third Party Support	Contractors	Use of contractors to implement energy conservation measures found by other people. Strategies includes: New physical installs completed by controls and mechanical contractors; contractors to complete retrofits.	2	0	0	0%
MBCx Implementation Phase	Third Party Support	Service Providers	Use of service providers or consultants for services such as analysis; installation of FDD; etc. Strategies include: Service provider identifying controls and capital improvements; service provider used to configure EMIS; service providers used when in-house staff does not have capacity to seek out and resolve issues. Can lead to challenges when service providers reporting faults, but not helping prioritize or find resolutions; service providers reportedly more expensive than in-house staff.	19	5	1	26%