Work Order Prioritization Using Neural Networks to Improve Building Operation

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ABSTRACT

Facility management involves a variety of processes with a large amount of data for managing and maintaining facilities. Processing and prioritizing work orders constitute a big part of facility management, given the large number of work orders submitted daily. Current practices for prioritizing work orders are mainly user-driven and lack consistency in collecting, processing, and managing a large amount of data. Decision-making methods have been used to address challenges such as inconsistency. However, they have challenges, including variations between comparisons during the actual prioritization task as opposed to those outside of the maintenance context. Data-driven methods can help bridge the gap by extracting meaningful and valuable information and patterns to support future decision-makings. Through a review of the literature, interviews, and survey questionnaires, this research explored different industry practices in various facilities and identified challenges and gaps with existing practices. Challenges include inconsistency in data collection and prioritizing work orders, lack of data requirements, and coping strategies and biases. The collected data showed the list of criteria and their rankings for different facilities and demonstrated the possible impact of facility type, size, and years of experience on criteria selection and ranking. Based on the results, this research proposed a methodology to automate the process of prioritizing work orders using Neural Networks. The research analyzed the work order data obtained from an educational facility, explained data cleaning and preprocessing approaches, and provided insights. The data exploration and preprocessing revealed challenges such as submission of multiple work orders as one, missing data for certain criteria, long durations for work orders' execution, and lack of correlation between collected criteria and the schedule. Through hyperparameter tuning, the optimum neural network configuration was identified. The developed neural network predicts the schedule of new work orders based on the existing data. The outcome of this research can be used to develop requirements and guidelines for collecting and processing work order data, improve the accuracy of work order scheduling, and increase the efficiency of existing practices using data-driven approaches.

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GENERAL AUDIENCE ABSTRACT

Facility Management (FM) is a profession that integrates various disciplines to ensure the comfort and safety of the occupants, efficiency of the built environment, and functionality of the building while meeting the main objectives of the owners. It involves various functions, including space management, communication, contract management, inspection, etc. Among many of these FM functions, maintenance-related tasks occupy 79% of the facility managers' responsibilities and %60 of the building cost in its whole lifecycle (design, construction, and operation). Prioritizing and processing work orders constitute a big part of facility maintenance management and requires a large amount of information submitted with hundreds of orders that need to be prioritized and turned into actions on a daily basis.

Although vast amounts of work orders are submitted daily, the process of prioritizing orders has been done manually or partially through management systems rendering the process very challenging. The existing practices are highly dependent on the extent of knowledge, experience, and judgment of responsible staff available, are impacted by human cognitive workload and coping strategies and are challenged by inconsistency in data collection and uncertainty in decision-making. Delays in processing work orders can lead to asset downtimes and failure impacting occupants' comfort, health, and safety while increasing the cost of operation. Additionally, based on the results of previous studies, the alternative comparison for prioritizing work orders varies and is more realistic when performed during the actual work order prioritization task as opposed to outside of the maintenance context.

Artificial Intelligence (AI) and Machine Learning (ML) algorithms have provided opportunities to benefit from the historical data collected and stored by the facilities. Artificial Neural Networks, one type of ML models, mimic the behavior of the human brain by learning from previous processes and information collected allowing computer programs to automatically process new information received. Since a large number of work

orders are generated and stored by facilities, such methods can be used to address the challenges with existing practices to reduce errors, downtimes, and asset failures and improve the operation of the buildings by supporting automation within the systems.

This dissertation first aims to explore the existing practices for processing and prioritizing work orders and identifying their gaps and challenges. Second, it investigates the implementation of Artificial Neural Networks (ANNs) to automate the prioritization of future work orders. The ANN is one type of machine learning model which reflects and mimics the behavior of the human brain to understand the relationship between a set of data allowing computer programs to solve complex problems. This research will improve the existing practices for processing work orders by allowing the automation of future work order prioritization. It also provides the basis for the development of data requirements to further support existing practices.

To my loving parents, Ali and Esmat

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AHP	Analytical Hierarchy Process
ANN	Artificial Neural Network
ANP	Analytic Network Process
AR	Augmented Reality
ASC	Associate School of Construction
CAFM	Computer Aided Facilities Management
CMMS	Computerized Maintenance Management System
FM	Facility Management
FMEA	Failure Modes and Effects Analysis
IFMA	International Facility Management Association
IRB	Institutional Review Board
ML	Machine Learning
MR	Mixed Reality
QA	Quality Assurance
QC	Quality Control
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution

CHAPTER 1: INTRODUCTION

Facility management (FM) “is a profession that encompasses multiple disciplines to ensure functionality, comfort, safety, and efficiency of the built environment by integrating people, place, process, and technology” (IFMA, n.d.). FM has also been defined as an integrated approach for operating and maintaining buildings to meet the main objectives of organizations, facility managers, owners, and end users (Chen et al., 2018). Maintenance occupies 79% of the facility managers’ responsibilities (Besiktepe et al., 2020; Wang & Piao, 2019). Maintenance is defined as “all the actions which aim to restore any functionality of a product within its lifecycle” (Palmarini et al., 2018, p.215). Facility management takes about %60 of the building cost in its whole lifecycle (Guillen et al., 2016). Different references reported a high percentage of maintenance costs (average $1.40-1.85 per sq ft) considering the building lifecycle cost (Chen et al., 2018; Sadeghi et al., 2018; Thabet & Lucas, 2017).

Facility managers are continuously under pressure to reduce costs and maximize the efficiency and productivity of staff, forcing them to balance facilities’ requirements against financial limitations (Roper & Payant, 2014). Furthermore, one of the main goals of FM is to improve the economic life of buildings (Islam et al., 2019). Poor facility performance is mainly due to cost constraints, lack of funding, budget cuts, as well as maintenance management (Besiktepe et al., 2020). Therefore, facility managers are constantly looking for new approaches to enhance efficiency and productivity (Irizarry et al., 2013). FM involves a huge number of assets and equipment with a large amount of data associated with them, requiring facility managers to develop plans for capturing, storing, and analyzing the data to respond to the organization’s goal (IFMA, 2021). Lack of proper decision-making approaches and lack of a maintenance plan can increase the cost of operation from 5 to 20 percent, influencing the schedules, performance (O'Connor et al., 2004), and quality of FM (Islam et al., 2019). A reasonable management plan is needed to effectively utilize facility information and help FM staff to reduce costs associated with O&M. A minor change in facility management, such as choosing the proper maintenance type and time, can greatly impact the cost, condition, and performance of the facility (Grussing & Liu, 2014).

Current FM practices also have challenges associated with data loss, time wasted searching for information, lack of interoperability, inconsistency, etc. (Sadeghi et al., 2018; Martínez-Rojas et al., 2016). FM requires an approach in which there is access to accurate and reliable information about buildings systems as well as building components (Sadeghi et al., 2018). Information stored in facility management systems such as AiM (AssetWorks, n.d.) or Maximo (Projetech, n.d.) is critical for O&M. To overcome the challenges, proper data management tools and technologies should be implemented into the FM process (Martínez-Rojas et al., 2016). Additionally, considering and including different sources of information for FM can improve the operation of the facility (Lavy et al., 2019). At the same time, it is significant to update the information and process (Brundage et al., 2019; Martínez-Rojas et al., 2016) to improve decision-making and thus, enhance maintenance tasks, customer satisfaction, and safety while reducing risks and costs of failures (Salem & Elwakil, 2018).

A comprehensive literature review and analysis were conducted (Ensafi & Thabet, 2021) between August 2019 and November 2020 using the ASCE and EBSCO databases. The inclusion criteria were English journals and conference papers published between 2012 and 2020. Papers focusing on operation, maintenance, BIM, and data management for FM were identified in the first search resulting in identifying 254 relevant articles. After removing duplicates, 197 articles remained. Abstracts of these 197 articles were reviewed to remove irrelevant articles, including articles focusing on computer science aspects. Upon completion of abstract reviews, 126 articles were selected. Based on the literature review, three FM challenges were identified: processing work orders, access to relevant data in the field, quality control (QC), and quality assurance (QA).

1.1 Facility Management Challenge Areas

1.1.1 Processing Work Orders

One challenge faced by facility managers and staff is prioritizing work orders and creating schedules. Work order processing is a significant part of facility management in terms of recording and reporting all maintenance tasks (Lavy et al., 2019). Large numbers of work orders are submitted daily, yet there are no consistent standardized approaches for performing the process (Lukens et al., 2019). Paper-based information is still used for transferring information, although maintenance systems such as computerized maintenance management systems (CMMS) and computerized aided facility management systems (CAFM) are available (Cheng et al., 2020). The work order processing greatly depends on staff experiences and the extent of knowledge (Cao et al., 2015; Tam et al., 2017), as well as the number of staff available to process the orders (Beauregard & Ayer, 2019). Delays in processing can lead to asset failure and downtimes impacting the cost of operation and occupants' safety and satisfaction (Hong et al., 2020; Salem & Elwakil, 2018). Lukens et al. (2019) indicated that there is a need for the standardization of data captured as well as standardized definitions for creating, planning, scheduling, and executing maintenance work orders. Having access to proper and required data, as well as identifying critical factors and criteria that influence work order processing will help with providing a clear and standardized approach.

1.1.2 Access to Relevant Data

There are also challenges associated with identifying and making relevant data available to assist FM staff in performing maintenance in the field. Capturing and storing data from different sources in different formats create several challenges. First, challenges associated with identifying the most efficient way for presenting large amounts of data to field staff. Second, there are complications with selecting the most relevant data to present to the O&M staff for the task at hand. Third, some information is duplicated creating data overload (Chekryzhov et al., 2018; Irizarry et al., 2013). Fourth, such approaches create complexity for data exchange and retrieval, causing lack of interoperability (Martínez-Rojas et al., 2016). Fifth, it is challenging for FM staff to find an effective and productive process with limited resources, budget pressures, and tight schedules to address the requests and expectations (Cao et al., 2015). Sixth, providing a large amount of information to the user will lead to cognitive overload impacting the user performance (Abbas et al., 2020). Poor information management can negatively impact facility management activities by creating waste activities produced by providing more information than what is actually needed. This forces O&M teams to spend more time looking for relevant information, requiring excessive processing time and wasting resources (Yang & Ergan, 2017).

Furthermore, bombarding the receiver with a huge amount of information can cause a distraction by crowding relevant information with irrelevant data.

Information visualization has attracted attention during the past decade in terms of addressing different backgrounds and levels of understanding (Moreira et al., 2018; Webel et al., 2013). Maintenance is a knowledge-intensive task; therefore, using AR can reduce cognitive load, error, and time while increasing performance (Abbas et al., 2020; Hou et al., 2015). The gaps related to AR technologies have been linked to one of several content-related techniques of authoring, context-awareness, or interaction analysis (Del Amo et al., 2018; Erkoyuncu et al., 2017). In other words, there is a gap in having a framework for identifying, capturing, presenting, and managing required data that can be connected to the FM system (Del Amo et al., 2018). This drives attention to the importance of access of the right user to the right information with the right quality at the right time to enhance efficiency. Maintenance staff have different types of expertise and specific O&M responsibilities. To be more efficient, staff should have immediate access to pertinent asset information in a reasonable amount of time when they are in the field. Palmarini et al. (2018) have demonstrated the benefits of using AR glasses for improving maintenance performance and decision-making. They believe that AR solutions need to consider context requirements and different visualization methods to provide more suitable results to the user. Screens are often overloaded with information leading to less tendency to implement technologies into the O&M process (Chekryzhov et al., 2018).

1.1.3 Quality Assurance and Quality Control

A third FM set of challenges relate to quality control and quality assurance strategies of FM processes. Traditional QA/QC is based on collecting data, creating reports, and manually entering the information into the FM system. Such processes require a significant amount of time which affects both quality and cost. Additionally, shortage of labor or experienced staff available for QA/QC can always generate challenges for the FM. On the other hand, the quality of work done by FM staff should always be evaluated. Actively monitoring and analyzing the accuracy of maintenance steps are significantly important. Although many studies have considered the significance of QA/QC during construction and before transferring information and documents to facility management, the importance of continuous QA/QC after construction has not been considered sufficiently (Zaher et al., 2018; Chalhoub et al., 2018; Martínez-Rojas et al., 2016; Zollmann et al., 2014). Facility systems have been used to store information related to O&M; however, they lack the ability to support data collection, data entry, and data retrieval (Ammari & Hammad, 2014). Analyzing the performance of the staff should be part of the maintenance process. The information should be collected from the maintenance process and should be managed properly in order to be analyzed and used for performance enhancement. Additionally, real-time feedback should be considered (Westerfield et al., 2015) in addition to using multimodal interaction methods to track the interaction with the objects to assist with recording staff performance as well as maintenance duration (del Amo et al., 2018). Image processing has been suggested as a method for processing and analyzing productivity and performing QA (Karji et al., 2017).

The three major challenges discussed are highly dependent on a large amount of interrelated information. Farghaly et al. (2018) suggested the need for a common database to collect and store asset information. Using such a data-driven decision-making approach will allow users to be able to connect different tasks within the FM and increase interoperability. Out of the three challenges identified, processing work orders was selected for further research (Figure 1.1). The next section provides a summary of previous studies in this area and the existing gaps and challenges.

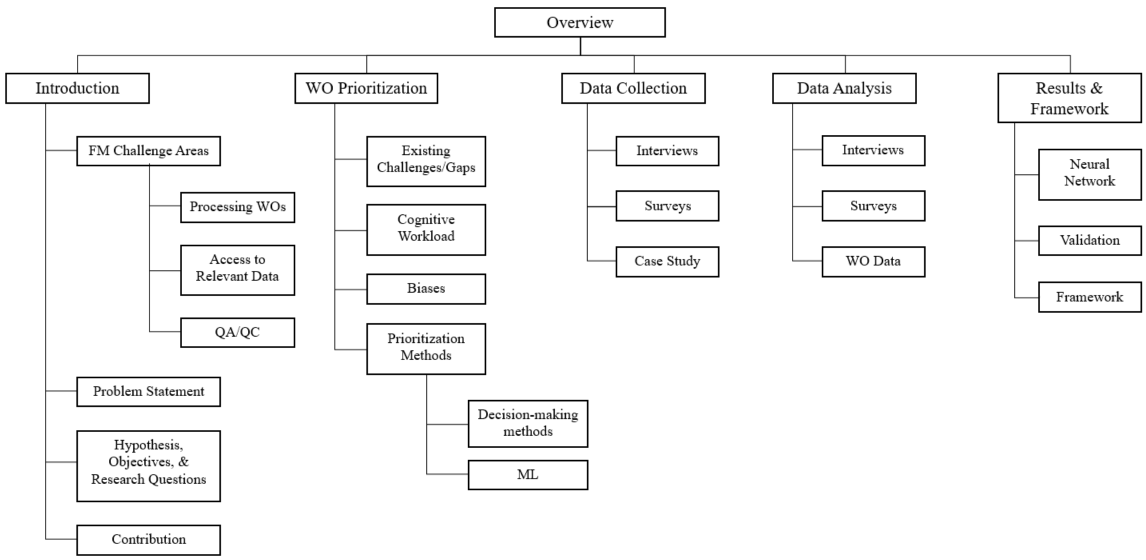

Figure 1.1.An overview of the areas covered in the dissertation

1.2 Summary of Methods Adopted

Although a vast amount of work orders are submitted daily (Mo et al., 2017), the process has been done manually or partially through management systems. There are no clear approaches for performing the process, and every facility has its own strategy and approach. In traditional work order processing, work orders are requested by either occupants or O&M staff through phone calls, emails, or specialized systems and are received by the maintenance department (Mo et al., 2017). The staff will use their experience, knowledge, and judgment to analyze the work orders, make decisions, and assign them to the qualified technician (Bouabdallaoui et al., 2020; Cao et al., 2015; Roper & Payant, 2014). The traditional approach has many challenges. First, this approach requires high-quality training to avoid uncertainty and poor performance. Second, the extent of knowledge and experience of the staff who analyze the service requests can influence the work order processing (Cao et al., 2015; Tam et al., 2017). The lack of knowledge about asset performance will lead to errors and asset failure. The equipment failure will force the facility managers to replace the assets, impacting the cost of O&M (Salem & Elwakil, 2018). Asset failure, downtimes, and shutdowns can lead to extreme revenue loss every year (Bayasteh et al., 2019). Third, experienced individuals with good knowledge of the facility are currently selected for processing work orders. However, the selected individuals might leave the facility or retire, and their expertise and knowledge will leave with them. As a result, the expertise and knowledge will not be transferred to the next individuals responsible for processing work orders. Fourth, the process requires an adequate number of staff to fill the shifts for receiving work orders, and there are mostly more work order requests than available staff for addressing them (Beauregard & Ayer, 2019). Making decisions and responding to the huge number of requests demand intensive labor hours. Consequently, the process can be affected by human errors such as underestimating an important criterion for processing work orders due to cognitive workload or decision-making biases (Galy et al., 2012). Late responses can again cause asset failure, which will negatively impact the environment, safety, as well as occupants' satisfaction (Bouabdallaoui et al., 2020; Mo et al., 2017; Salem & Elwakil, 2018). Based on the previous studies (Table 1.1), multiple gaps and challenges have been identified and factors for enhancing the process have been suggested.

Table 1.1. Challenges, gaps, and suggestions for work order processing

	Description	References
Gaps	Lack of comprehensive list of factors.	Beauregard and Ayer (2019)
	Excluding different types of maintenance	Chen et al., 2018 Beauregard and Ayer (2019)
	Overlooking Client/occupant/owner's satisfaction	Mo et al., 2017 Cao et al., 2015
	Excluding budget	Besiktepe et al., 2020
	Lack of information requirements	Yang & Ergan, 2017 Lavy et al., 2019
	Not considering major repairs such as emergency or critical breaks	Beauregard & Ayer (2019)
	Generalizing one solution to different types of facilities	Besiktepe et al. (2020) Chong et al. (2019)
	Focusing on single maintenance tasks/work crew	Chen et al. (2018)
Challenges	Inconsistency in data input and structure	Yang & Bayapu (2019) Lukens et al. (2019)
	Interoperability issues	Yang & Bayapu (2019)
	Continuous data collection and update	Ensafi & Thabet (2021)
	Multiple data entry/ data duplication	Chekryzhov et al. (2018)
	Dependency of work order processing on staff experiences and extent of knowledge	Cao et al. (2015) Tam et al. (2017)

	Number of staff available for processing WOs	Beauregard & Ayer (2019)
	Processing work orders for different maintenance crews simultaneously	Chen et al. (2018)
	Cognitive overload impacting the user performance	Galy et al. (2012)
	Delays in processing leading to asset failure and downtimes	Hong et al. (2020) Salem & Elwakil (2018)
Suggestions	Considering organizational needs when identifying and prioritizing the list of influential criteria	Besiktepe et al. (2020) Chong et al. (2019) Yang et al. (2018)
	Understanding and identifying costly assets	Islam et al. (2019)
	Identifying assets that are difficult to maintain	Islam et al. (2019)
	Considering the entire facility system as well as the association between different equipment	Wang & Piao (2019)
	Having a well-defined organizational priorities and goals to remove subjective judgements	Chong et al. (2019)
	Considering the source of funding and funding mechanism	Sadeghi et al. (2018)
	Understanding and identifying information requirements to create standard rules for capturing and storing work orders	Lavy et al. (2019) Lukens et al. (2019) Yang & Ergan (2017)
	Need for a common database	Farghaly et al. (2018)
	Update and adjust the system through building lifecycle	Brundage et al. (2019) Martínez-Rojas et al. (2016)

Strategic decision-making requires individuals to select an optimal alternative from a set of available options. The alternatives often have various attributes complicating the decision-making process. Pairwise comparisons allow reducing the complication by breaking down the problems into tractable ones (Dixit, 2018). To address some of the challenges mentioned above, different statistical methods have been used by various studies for prioritizing a set of alternatives for facility management. Ohta et al. (2018). They implemented Analytical Hierarchy Process (AHP) methodology in their study to choose the proper maintenance strategy for plant maintenance based on cost, quality, safety, value added, and viability. Chemweno et al. (2015) in which they used the Analytic Network Process (ANP) method for selecting the appropriate risk assessment techniques. Layzell and Ledbetter (1998) used the Failure Modes and Effects Analysis (FMEA) methodology to reduce risk of failures in automotive cladding. Ding et al. (2014) implemented Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in their study for selecting the optimal maintenance policy. Selim et al. (2016) used a combination of TOPSIS and FMEA to address the cost of maintenance in an international food company.

Due to the rapid improvement of technologies used for facility management, more complicated and larger amount of data are created and are available to facility managers (Cao et al., 2015). The concept of big data can help with extracting meaningful and valuable information from the available data (Yang & Bayapu, 2019). Different studies have benefitted from historical data and data analytics for facility management. Examples of such studies are as follows. Besiktepe et al. (2019) used historical work order data in educational institutions to identify the frequency of maintenance activities and explore possible relationship between building age and type and maintenance activities. Their results indicate that electrical, HVAC, and plumbing have the highest maintenance frequency among all building systems. Also, no relationship was found between building age and type and the maintenance activities. The researchers have suggested including subcategories for maintenance activities to reach better results from maintenance data analysis. Yang et al. (2018) developed a failure mode and effect analysis (FMEA) method using data mining to address the HVAC maintenance issues. They used the work order data from building energy management systems. Based on their results, the analysis of work order data can help with determining parameters for FMEA models while it can also help with determining the high impact failures. Furthermore, their results indicate that the is a relationship between frequency of faults and building type.

Data analytics methodologies can also be used to process and investigate the data, find patterns, and drive conclusions from the collected data to benefit the facilities and support their decision makings (Assaf et al., 2020; Jiang et al., 2020). Facility managers can use different tools and platforms to capture information, perform analysis, and draw conclusion on past performance while also anticipating future trends using Artificial Intelligence (AI) and Machine Learning (ML) (IFMA, 2021). Machine learning is “the process of training a computer model on a training dataset to perform a certain task so that it will be able to perform that exact task when given new data it had not encountered before" (Assaf et al., 2020, p.173). The use of AI and ML allows prescriptive analysis which supports complex decisions and improves efficiency while reducing the need for human input (IFMA, 2021). Recently, an increasing number of studies are adopting AI techniques and ML algorithms to address design, construction, and facility management challenges (Awada et al., 2020; Feng et al., 2017; Tabrizi et al., 2012). Researchers have implemented AI and ML to address different aspects of building operation phase including air quality (Xie et al., 2020), energy consumption (Hajj-Hassan et al., 2020; Lu & Feng, 2020; Murrieum et al., 2020; Wang & El-Gohary, 2020; Roth et al., 2019; Ahmad et al., 2017; Dedemen et al., 2017; Hsu, 2015), and cost analysis (Liu et al., 2020; Gao et al., 2019; Krstić & Marenjak, 2017; Au-Yong et al., 2014).

Studies that considered the implementation of ML for addressing challenges related to the work orders are as follow. Assaf et al. (2020) used machine learning algorithms to address predictive maintenance by analyzing occupants' complaint data. They implemented text mining to identify the most frequent complains of the occupants. Based on their results, complains related to air conditioner were among the most frequent complains. They then used ML to develop a model to predict the future complains in order to help FM professionals to plan ahead. Kolokas et al. (2018) used the data collected from sensors and implemented artificial neural network for detecting and predicting faults in industrial equipment. Their results support predictive maintenance. The ML classifiers used in their study allowed them to predict equipment failures five to ten minutes before the breakdown using the changes occurred in the data collected by the sensors. However, this timeframe is not sufficient for timely responds. Canizo et al. (2017) implemented random forest to their workflow to predict wind turbines failures to address predictive maintenance. Although their results presented an overall success in predicting failures, they believe that there is a need for accuracy improvement. Lempert et al. (2016) implemented machine learning for prioritizing road repair tasks according to optimal utilization of resources. Their proposed solution is based on defect recognition and classification methods. Cao et al. (2015) developed a framework using artificial intelligence to prioritize work orders based on both occupants' and facility managers' feedbacks. Abdelrahim and George (2000) implemented the neural network into the process of prioritization and selection of pavement maintenance strategy based on the level of alligator cracks, traffic volume, condition of the pavement, distress type, and road class. They believe that using their proposed network can accelerate the process while allowing the system to update over time.

Facility managers should implement analytics to determine appropriate measures based on their organization's objectives, determine data requirements, draw conclusions from the analysis, and plan accordingly (IFMA, 2021). Yang and Bayapu (2019) reviewed the challenges in implementing data analytics to facility management practices. Based on their results, inconsistency in data input and structure as well as interoperability issues are the main challenges identified in facility management. In order to be able to benefit from data-driven decision-making, facility managers should plan the process in detail to address inconsistency in data collection and processing. Valuable information about work orders can be collected from historical data as well as day to day data collected by the FM systems. The analysis of these data can help with enhancing the system to provide better output and improve the quality of the work performed.

Maintenance tasks can be prioritized by having access to necessary and proper resources such as time, tools, labor, etc. (Lavy et al., 2019). Identifying critical factors for prioritizing work orders can help us to propose an approach for automatically analyzing work orders and creating schedules for maintenance tasks. At the same time, using new technologies can assist facility managers in overcoming the time-consuming tasks and accelerating the process of FM (Irizarry et al., 2013).

1.3 Problem Statement

Generally, studies conducted on prioritization have used decision-making methods such as AHP to simplify the complication of decision-making by assigning weights to a set of criteria for prioritizing a set of alternatives. However, relying on these methods have multiple defects. First, humans don’t fill pairwise comparison matrices consistently. Second, not all inputs can be reliable when the matrices are large. Third, the weight assigned to the criteria are subjective numbers outside of context. In other words, individuals would assign an importance number to each criterion relative to other criteria. However, based on the interviews conducted, the priorities given to the criteria might be different from when the priorities are given in the actual situation. Fourth, strategic decision-making requires individuals to select an optimal alternative from a set of alternatives. Considering limited cognitive capacity in humans, it is not possible or realistic to select one attribute for each alternative and based on psychological studies, humans are not able to reliably compare multiple pairwise alternatives at the same time due to information overload. Consequently, overloading human operators with information impacts their decision-making.

Therefore, using the data from previously prioritized work orders and schedules and implementing data analytics to identify the associated weight of each criterion can assist with prioritization of future maintenance work orders. It can also help with defining data requirements and hence increasing consistency while reducing processing time. As discussed above, neural networks have been used in some fields such as road maintenance to prioritize a set of alternatives. With defined framework, the neural network can be used to address the maintenance of building facilities by supporting the automation of maintenance work order processing. Among the different ML methods, neural network would be a better fit for this study because first, neural networks can be used with higher dimensional data corresponding to including more criteria. Such approach allows considering all influential criteria in decision-making leading to more accurate results. Second, neural network allows determining the right number of criteria based on the concept of overfitting/underfitting. Third, they can calculate the weights of the criteria based on the interaction between different criteria and the arrangement of neurons. Fourth, neural network can create the best arrangement itself to make accurate decisions without the need to specify the interaction by the modeler (defining rules in advance) while other ML algorithms require human intervention. fifth, neural network can be modified and adjusted based on new inputs. If the facility staff make any changes to the rankings and schedules created, the system can automatically learn from the changes occurred and implement that to the future prioritization. Such approach avoids manual changes providing a more practical solution over a longer time span while improving the performance of the system. Implementing data-driven decision-making using neural networks can therefore address human limited cognitive capacity and reduce cognitive workload by performing main part of prioritization task allowing FM staff to focus on abnormalities and emergency situation requiring higher decision-making skills. It can also reduce coping strategies. Additionally, processing work orders considering previous input from multiple users allows required adjustments and hence minimization of judgment and cognitive biases' influence.

The results of all the factors mentioned above will extremely impact the productivity of facilities by providing higher quality services. It will also increase occupants' satisfaction by timely responses to the work orders and reducing failures and downtimes.

1.4 Hypothesis, Research Objectives, and Research Questions

1.4.1 Research Goal

The goal of this research is to enhance the process of prioritizing work orders and creating schedules by developing a framework which benefits from neural network to automatically prioritize work orders.

1.4.2 Hypothesis

The researcher hypothesis is that the process of prioritizing work orders can be automated using neural networks to support the efficiency and accuracy of work order prioritization while enhancing staff performance. Developing an automated system can also support the decision-making and consistency in terms of data collection and criteria used for processing work orders.

1.4.3 Objectives

There are five main objectives for this study.

1. Identify gaps and challenges in existing processes for processing maintenance work orders.

2. Determine the comprehensive list of criteria used for prioritizing work orders.

3. Investigate the possible impact of facility type, facility size, and years of experience on processing and prioritizing work order.

4. Identify data overlaps and information requirements for different stages of work order processing to support data-driven decision making.

5. Automate the prioritization of work orders using neural network to support processing work orders, increase consistency and accuracy, and enhancing staff performance by reducing cognitive workload.

1.4.4 Research Questions

Table 1.2 present the research questions considered for this study.

Table 1.2. Research questions

Q1	What are the similarities and differences between literature review and existing industry practices in terms of processing and prioritizing work orders?
Q2	What is the comprehensive list of criteria and their associated rankings for prioritizing maintenance work orders? Do facility type, facility size, and years of experience impact the list and/or ranking of criteria?
Q3	What is the data overlap between the information used for processing work orders and the information collected following the maintenance task?
Q4	Can neural network prioritize work orders based on previous schedules created to support accuracy, efficiency, and consistency?
Q5	What is the most efficient neural network structure for prioritizing maintenance work orders?

1.5 Research Methodology

The research methodology considered for this study is a mixed method covering both qualitative and quantitative data collection to better support the arguments stated in this research. The methods considered include unstructured and semi-structured interviews, questionnaire survey, and work order data of an educational institution (Figure 1.2).

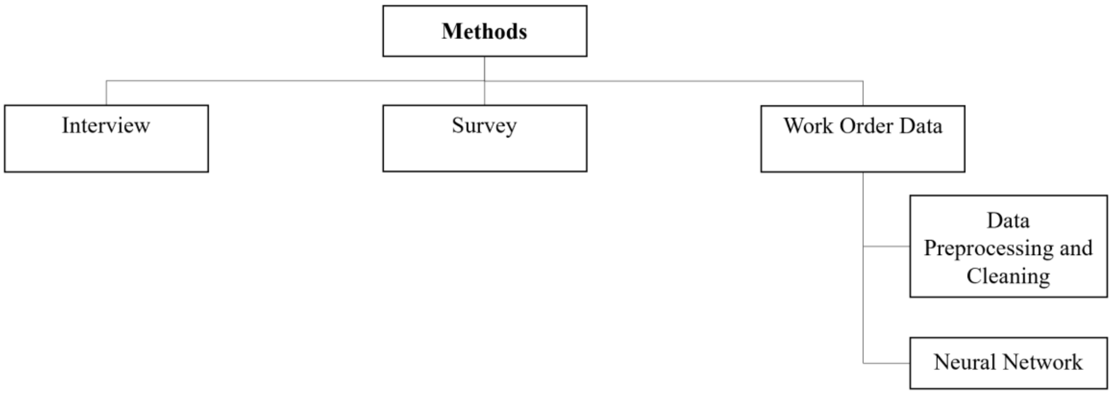

Figure 1.2. Summary of methods

Through the interviews (chapter 3), and questionnaires (chapter 4), existing practices for processing maintenance work orders are captured and their gaps and challenges are identified. Additionally, the relationship between different factors in processing work orders are identified and information requirements are determined. Following the results of the data collection, the work order data of an educational facility is used to test and validate (chapter 5) the implementation of neural networks for addressing the existing gaps.

1.6 Research Contribution

Research contributions are as follow:

1) Conduct an in-depth data collection (survey) to provide empirical scientific evidence specially in the topic of prioritizing work order. This research will be based on actual data collected.

2) Develop a data-driven methodology to automate the prioritization of maintenance work orders

1.7 Organization of the Dissertation

The dissertation is structured using a manuscript-based format and organized into four chapters and four manuscripts in addition to the conclusion chapter. The second chapter (manuscript 1) is published in a refereed conference proceedings and the other three are submitted to or are published in academic journals. The following describes a short summary of each chapter (manuscript) and its relation and transition to the next chapter.

The chapter 2 (manuscript 1) is published in proceedings of the Associate Schools of Construction (ASC) conference (Figure 1.3, manuscript 1). It covers three identified challenge areas in facility maintenance practices. The areas include work order processing, access to relevant information, and quality control and quality assurance procedures. The chapter proposes a conceptual framework for addressing the three challenges and for preparing a solution to combine and connect the three areas. The chapter concludes by highlighting the focus on work order prioritization in subsequent research and chapters. The challenges and gaps identified in work order prioritization are further studied in the chapter 3 (manuscript 2) and chapter 4 (manuscript 3) to collect the full list of criteria and their ranking for studying data driven methods in chapter 5.

The chapter 3 (Figure 1.3, manuscript 2), submitted to a journal, presents the results of literature review conducted to investigate current practices adopted by different facilities for processing work orders. It also determines various gaps and challenges within those processes including challenges related to cognitive workload and coping strategies as well as different cognitive biases in strategic decision-making. The chapter then uses the result of 17 unstructured and semi-structured interviews to highlight the existing gaps and challenges in maintenance work order prioritization and present the differences between literature and interviews. The chapter concludes with suggestions on using data-driven decision-making methods as opposed to user-driven methods to address the challenges. To be able to further study the existing practices, criteria selection, criteria ranking among different facility experts, and the implementation of the decision-making methods, this study is followed by the next chapter (chapter 4, manuscript 3) which contains the results of survey questionnaires covering data from higher number of individuals and a wider range of perspectives and practices.

The chapter 4 (Figure 1.3, manuscript 3), submitted to an academic journal, reviews the decision-making methods adopted by other studies to prioritize a set of alternatives to address the existing user-driven challenges. It also presents the results of a survey conducted between August to November 2021 using Qualtrics platform to study the process taken by different types of facilities for prioritizing work orders. The results of the survey are used to further verify findings from interviews, identify impact of external factors such as years of experience, type of facility, and size of facility on criteria selection and ranking, and investigate data overlap between different phases of work order processing. The chapter also explores the implementation of a decision-making method for prioritizing work orders and discusses their challenges. The chapter concludes with suggesting the implementation of artificial intelligence and machine learning methods to benefit from historical data collected to determine correlation between different criteria used for processing work orders, learn from the prioritization of previous work orders, and automatically prioritize future work orders.

The chapter 5 (Figure 1.3, manuscript 4), submitted to an academic journal, uses records of maintenance work orders requests and prioritized schedules from an educational facility to implement neural networks for work order prioritization. The list of criteria used are based on the survey questionnaire conducted in previous chapter as well as discussion with the facility regarding the most used criteria in their facility. The chapter describes the steps for preprocessing and cleaning the data and present the correlation identified between the criteria used. The chapter also provides the most efficient and accurate neural network configuration for prioritizing the maintenance work orders using the existing criteria in the FM system of the educational facility discussed. Using neural networks over other machine leaning methods allows the model to learn itself as opposed to writing rules for the model. As processing maintenance work orders is part of critical thinking, such approach allows learning from the previous operators thought process to provide a more practical solution for processing future work orders.

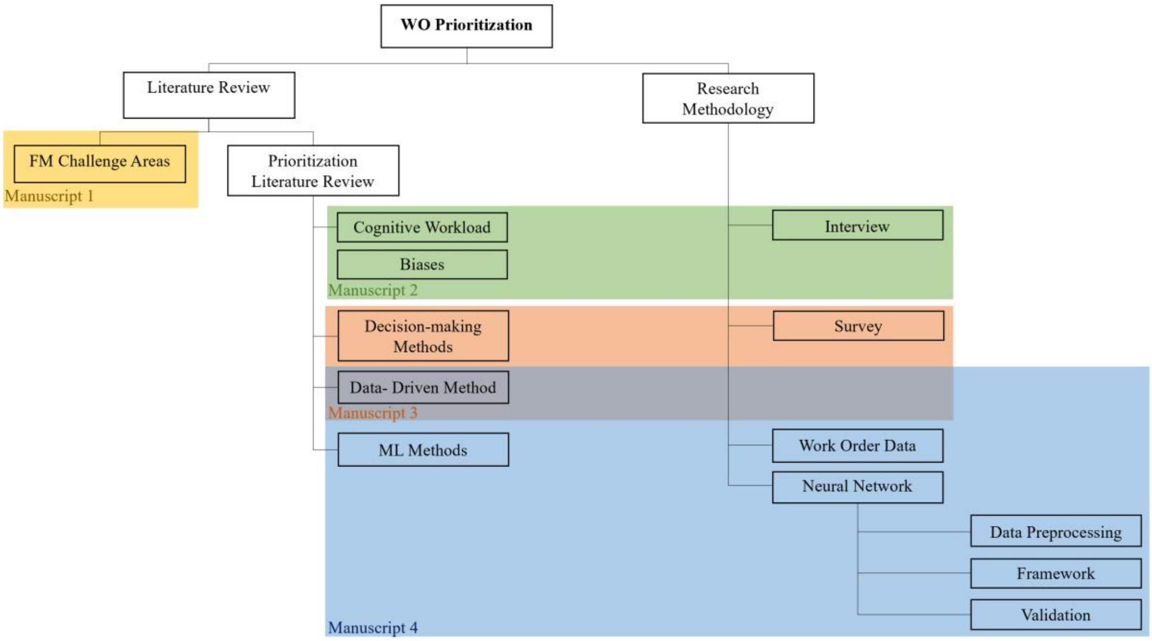

Figure 1.3. Dissertation structure

CHAPTER 2: CHALLENGES AND GAPS IN FACILITY MAINTENANCE PRACTICES[1]

2.1 Abstract

Facility management involves a variety of processes with a large amount of data for managing and maintaining facilities. Improved and emerging technologies available to facility managers have provided opportunities for easier access and management of the data allowing for more effective and efficient operation and maintenance. The concept of big data can help with extracting meaningful and valuable information from the available data. Current facility management practices and processes have many data management challenges, including data loss, time wasted for searching information, lack of interoperability, and so on. Lack of proper decision-making approaches and lack of maintenance planning can increase the cost of operation, influencing the quality of facility management. To effectively overcome these challenges and gaps, proper data management approaches and tools should be implemented. A structured literature review was conducted to identify challenges and gaps in three key facility processes: processing work orders, timely access to relevant data during field maintenance operations, and quality control/quality assurance of field tasks. This chapter provides an overview of the three key processes, summarizes the challenges and gaps identified for each key process and proposes a framework to improve on the execution of these processes and enhance facility management decision making.

Key Words: Operation & Maintenance, Work Orders Processing, Lifecycle Data, QA/QC, Augmented & Mixed Reality

2.2 Introduction

Facility management (FM) is an integrated approach for operating and maintaining buildings to meet main objectives of organizations, facility managers, owners, and end users. Facility management constitute more than half of the building cost in its whole

[1] Ensafi, M. & Thabet, W. (2021). Challenges and Gaps in Facility Maintenance Practices. EPiC Series in Built Environment, 2, 237-245.

lifecycle. Operation and maintenance (O&M) accounts for about 80 to 85 percent of capital project dollars (Thabet & Lucas, 2017) and maintenance occupies most of the facility managers' responsibilities. Maintenance can be defined as "all the actions which aim to restore any functionality of a product within its lifecycle" (Palmarini et al., 2018, p.215).

Facility managers are continuously under pressure to reduce costs and maximize the efficiency and productivity of staff forcing them to balance in facilities' requirements against financial limitations. Therefore, facility managers are constantly looking for new approaches for enhancing efficiency and productivity (Irizarry et al., 2013). FM involves a huge number of assets and equipment with a large amount of data associated with them. Current FM practices have challenges associated with data loss, time wasted for searching for information, lack of interoperability, and data inconsistency (Yang & Bayapu, 2019). FM requires an approach in which there is access to accurate and reliable information about building systems as well as building components (Sadeghi et al., 2018). Lack of proper decision-making approaches and lack of a maintenance planning can increase the cost of operation from 5 to 20 percent, influencing the schedules and quality of FM (Islam et al., 2019). A reasonable management plan in addition to proper data management tools and technologies is needed to effectively utilize facility information, update the information and process, and help FM staff to reduce costs associated with O&M. A minor change in facility management can greatly impact the cost, condition, customer satisfaction, safety and performance of the facility (Salem & Elwakil, 2018).

As part of a broader research investigation that included all the above references, a literature review and analysis was conducted between August 2019 and November 2020 and included the ASCE and EBSCO databases. The inclusion criteria were English journals and conference papers published between 2012 and 2020. Papers focusing on facility management, BIM, and data management were searched resulting in identifying 254 relevant articles. After removing duplicates, 197 articles remained. Abstracts of these 197 articles were reviewed to remove irrelevant articles including articles focusing on computer science aspects. Upon completion of abstract reviews, 126 articles were selected, and based on the number of articles addressing the challenges as well as possible connectivity between the challenges, three major challenge areas in FM were identified: processing work orders, timely access to relevant information in the field, and proper approaches for quality assurance and quality control of field tasks. Using a second restricted search with keywords that included: work order, prioritize, augmented reality, mixed reality, quality control, and quality assurance, more papers were added to the list. After removing the studies focusing on areas other than maintenance (e.g., safety), a final list of 83 papers was left. The 83 papers were fully reviewed by the researchers. Due to the limitation of the size of this paper, the most relevant and representative references were selected resulting in a final list of 33 papers. The PRISMA guideline was used to inform the overall approach (Figure 2.1). However, since this study is not a full systematic review, it does not fulfill all the aspects of the PRISMA guideline.

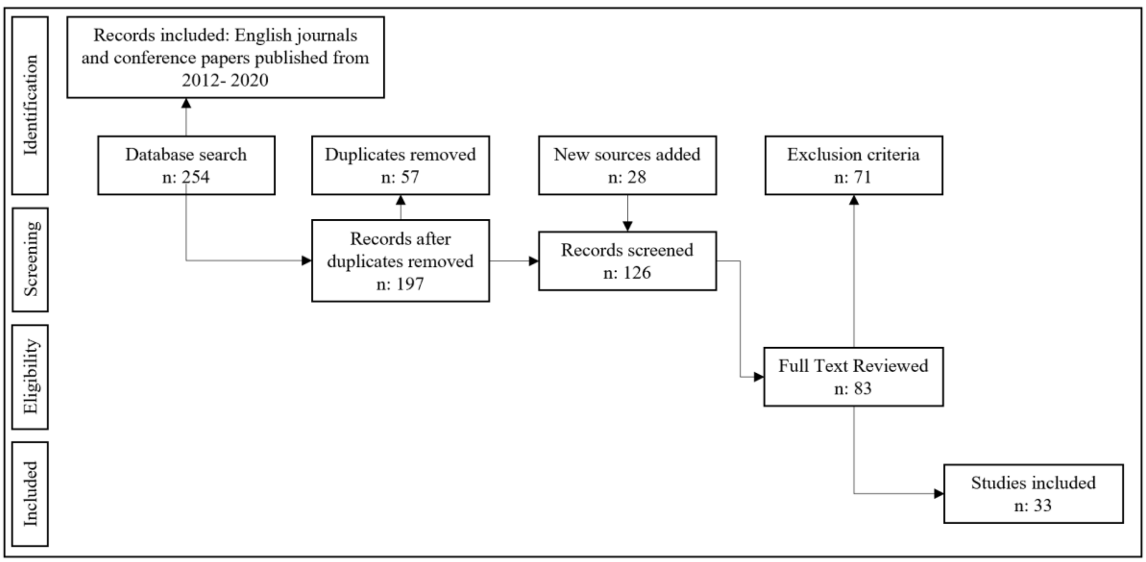

Figure 2.1. Search process (adapted from PRISMA)

This chapter will first provide an overview of the three challenges identified from the comprehensive literature review conducted. The chapter then proposes a framework with an integrated solution to address the three challenge areas. The proposed framework uses a common database to support a unified decision-making data management approach for operation and maintenance of the facility.

2.3 Challenges and Gaps with Facility Management Processes

The following sections provides a description of the three major challenge areas with FM as identified from the literature review process.

2.3.1 Work Order Processing

One major challenge faced by facility managers and staff is prioritizing work orders and creating work order schedules. Work order processing is a significant part of facility management in terms of recording and reporting all maintenance tasks (Lavy et al., 2019). Large number of work orders are submitted daily, yet there are no consistent standardized approaches for performing the process. The work order processing greatly depends on staff experiences and extent of knowledge (Cao et al., 2014) as well as the number of staff available to process the orders (Beauregard & Ayer, 2019). Delays in processing work order can lead to asset failure and downtimes impacting the cost of operation, safety and satisfaction of occupants (Salem & Elwakil, 2018).

Identifying and having access to required data as well as critical criteria that influence work order processing will help with providing a clear and standardized approach. Besiktepe et al. (2020) identified the general criteria used for supporting maintenance decision making. They ranked the criteria to develop a multi criteria decision making model. Beauregard and Ayer (2019) used four factors of influenced group, building status, building usage, and institutional enablers to prioritize work orders for routine maintenance. Their study is focused on the relationship between facility condition and academic outcomes for K-12 education in the USA. Wang and Piao (2019) prioritized maintenance tasks for equipment components based on maintenance type and assessment of risk in terms of reliability, maintainability, economy, and detectability. Chong et al. (2019) reviewed the methods and factors used for prioritizing work orders. They categorized the factors into four groups of technical, financial, social, and political. Chen et al. (2018) explored the use of BIM combined with COBie as a geometric and semantic information repository to support FM decision making for creating maintenance work order schedules. Their proposed solution presented the existing condition of assets in the BIM model and is focused on four factors of problem type, emergency level, location, and optimal distance. Sadeghi et al. (2018) highlighted the importance of considering the source of funding and funding mechanism for maintenance decision makings in terms of capital renewal, renovation, upgrade, demolish, emergencies, etc. Salem and Elwakil (2018) determined the criticality of assets in healthcare facilities based on physical conditions, infection prevention, life safety, and revenue loss to prioritize budget allocation and reduce failure. Yang and Ergan (2017) explored required information that should be stored in BIM to automate HVAC troubleshooting. Eweda et al. (2015) created a condition assessment model considering space as the principal element for evaluation. Their model hierarchy is broken down to building type, space type, building categories, building systems, family type, and instance level. Cao, Song, and Jiang (2014) developed a framework to prioritize work orders based on feedback from both occupants and facility managers.

Based on the literature review conducted, nine factors or issues were identified that need to be considered to enhance processing of work orders. 1) Understanding and identifying information requirements will help facility managers to benefit from the systems used for FM (Yang & Ergan, 2017) while allowing them to create standard rules for capturing and storing work orders (Lavy et al., 2019). 2) It is important to identify assets that are more costly to operate and maintain (Islam et al., 2019). 3) Addressing the relationship between different equipment and systems in the facility in terms of their impact on each other can enhance the process (Wang & Piao, 2019).4) Based on findings by (Besiktepe et al., 2020; Chong et al., 2019), it is better to focus on one specific type of building than generalizing a single solution to different types of facilities since the organizational objectives need to be approximately close and related. Having a well-defined organizational priority will work as a guideline for all stakeholders and remove the subjective judgements. 5) 65% of generated service requests are submitted by occupants (Mo et al., 2017). Therefore, client/occupant’s satisfaction should be considered as one of the significant factors (Cao et al., 2014). 6) Not all studies have considered different types of maintenance. 7) Researchers have mainly focused on maintenance tasks completed using a single maintenance team (Chen et al., 2018). Multiple work orders completed simultaneously using multiple work crews should be considered when prioritizing and scheduling work orders.8) Budget is one of the main constraints for processing work orders and not considering it as a critical factor could prevent from providing optimal solutions. 9) Solutions proposed by previous studies are not designed in a way to allow updates and modifications required in the future.

2.3.2 Access to Relevant Information

There are challenges associated with identifying and filtering relevant and necessary data and making it readily available to assist FM staff while performing maintenance tasks in the field. Capturing and storing data from different information sources and in different formats create several challenges. Through the literature review, six challenges were identified. 1) There is a challenge associated with identifying the most efficient way for presenting large amounts of data to field staff (Cao et al., 2014). 2) there are difficulties with selecting the most relevant data to present to the O&M staff for the task at hand. 3) Some information is duplicated creating data overload (Chekryzhov et al. 2018). 4)Such approaches create complexity for data exchange and retrieval, causing lack of interoperability (Martínez-Rojas et al., 2016). 5) Staff performing maintenance tasks have different levels of knowledge and experience and thus, require different levels of information (Erkoyuncu et al. (2017). 6) Providing large amount of information to the user will lead to cognitive overload impacting the user performance (Abbas et al., 2020). Poor information management can negatively impact facility management activities by creating more information than what is needed (Yang & Ergan, 2017). This forces O&M teams to spend more time looking for relevant information, requiring excessive processing time while distracting the team by crowding the relevant information with irrelevant data.

Abbas et al. (2020) conducted a rebar inspection task to investigate the impact of using AR systems on cognitive load and performance of users. Their findings indicated that using AR can reduce cognitive load and time while increasing performance. They also concluded that the format of information presented can impact cognitive load and thus performance. Wang and Piao (2019) implemented AR into the process of O&M to provide information and guidance to the user.

Chekryzhov et al. (2018) addressed the issue of information overload using technological equipment and proposed possible solutions leveraging AR technology. Del Amo et al. (2018) indicated that the gaps related to AR technologies have been related to one of several aspects of content-related techniques of authoring, context-awareness, or interaction analysis. Del Amo et al. (2018b) studied data visualization using AR glasses and concluded that there is a gap in having a framework for identifying required data that can be connected to the FM system. Palmarini et al. (2018) demonstrated the limitations and benefits of using AR glasses for improving maintenance performance. They highlighted the importance of understanding the best approach for adapting the information to the user considering the environment and the task. Erkoyuncu et al. (2017) proposed a solution addressing context awareness and authoring. They sequenced the AR content based on the equipment and user's level of expertise. Hou et al. (2015) explored the use of AR to provide instruction for assembly and their findings supported shorter duration, less errors, and lower task load. Gheisari et al. (2014) developed a system using BIM and AR mobile apps to enhance FM by having easier and faster access to the location of the components. Irizarry et al. (2013) developed a mobile AR tool to allow access to FM information and decrease data overload. Webel et al. (2013) provided two different levels of instructions on AR glasses to support different experience levels.

Although AR has been introduced to the construction industry as a possible solution to reduce information redundancy, the format of information presented as well as amount of information presented to users still require more research. Screens are often overloaded with information leading to less tendency in implementing technologies into the O&M process (Chekryzhov et al., 2018). There exists a lack of research in automatic content contextualization. Considering context awareness can improve staff performance since the better and more accurate the information is presented, the better it will be transferred and utilized (Del Amo et al. ,2018). Additionally, it will reduce cognitive workload (Erkoyuncu et al., 2017). Maintenance staff have different levels of expertise and specific O&M responsibilities, Also, different maintenance tasks require different information. To be more efficient, staff should have immediate access to pertinent asset information in a reasonable amount of time in the field. Also, there is a gap in having a framework for identifying, capturing, presenting, and managing required data that can be connected to the FM system (Del Amo et al., 2018b). It is significant to identify what data is needed, how it should be captured and presented (Palmarini et al., 2018), and finally how it should be edited and managed for further updates to provide a more suitable results to the user.

2.3.3 Quality Control and Quality Assurance

A third major challenge identified from the literature relates to tracking and improving quality assurance (QA) and control (QC) of field tasks. Traditional QA/QC is based on collecting data and reports and manually entering the information into the FM system. Such processes require a significant amount of time and cost which impacts the QA/QC process. Additionally, shortage of labor or experienced staff can always result in challenges for the FM. Staff performance should always be analyzed and evaluated to identify gaps, modify the tools and training provided and enhance performance (del Amo et al., 2018b). Actively monitoring and analyzing the accuracy of maintenance steps are significantly important. Although many studies have considered the significance of QA/QC during construction more work is still needed to improve QA/QC during facility operations and maintenance.

Chalhoub et al. (2018) used mixed reality for construction QA/QC by comparing the 3D model with the actual building on-site. del Amo et al. (2018b) studied the integration of AR into the maintenance process, and they proposed a framework describing information type and formats as well as interaction modes for improving the efficiency of using AR for maintenance. Karji et al. (2017) reviewed the previous studies on integration of BIM, AR, and image processing in construction industry. They believe that image processing can be used to analyze productivity and perform QA. Liu and Zettersten (2016) highlighted the importance of having quality check. Martínez-Rojas et al. (2016) investigated the advantages of using information and communication technologies and their benefits for addressing quality control, progress monitoring, and costs. Westerfield et al. (2015) applied the use of AR into the assembly process by providing real-time feedbacks about the procedure. Fiorentino et al. (2014) used AR for presenting maintenance instructions and their results showed up to 92.4% error reduction and up to 79% time reduction. Kasprzak et al. (2013) conducted a survey and concluded that there is a gap in having enough QA/QC mechanisms for maintenance process standardization.

As discussed above, there is a need for controlling and analyzing the accuracy of the steps taken for training and maintenance. Although providing step by step instructions can reduce errors and asset failures, training and instructions should be continuously updated based on maintenance performance as well as operator level of experience and knowledge.

Researchers have highlighted the importance of automation in documentation and progress checking to reduce the time and staff required (Fiorentino et al., 2014). While AR glasses are used for remote collaboration to provide guidance and feedback, they can also allow QA/QC. Many available AR devices are able to recognize users' gesture (Cheng et al., 2020) and therefore, the interaction between user and content can be captured and analyzed (del Amo et al., 2018). Use of multimodal interaction methods have been suggested by previous studies to track the interaction with the objects to record time of maintenance as well as staff performance (del Amo et al., 2018b). Capturing movements can help to identify errors at the time of performance. Furthermore, due to the high number of maintenance tasks, not all the performed tasks are monitored and checked. With automated QA/QC, most of the tasks can be checked. Such strategies can help different facility managers to avoid double-checking and processing. It can also reduce their challenges by balancing the requirements of the facility with financial limitations.

2.4 Proposed Framework for Addressing the Challenges

Considering the three challenge areas discussed above, large amount of data is generated for various assets and is collected by different facility management systems. Therefore, there is a need for a common database to collect and store asset information (Farghaly et al., 2018) to allow connecting different facility management tasks and increase interoperability. Also, it is important to consider a continuous data collection within each task and continuous data collection moving from one task to the other. There is a need for identifying information requirements in terms of what data to collect at each step as well as data types and formats in order to increase consistency in data collection and exchange. Such approach will allow to benefit from informed and data-driven O&M decision making.

Figure 2.2 shows a proposed abstract theoretical framework defining a workflow that integrates three processes: work order processing, access and retrieval of critical and relevant maintenance data, and QA/QC using a common database to allow for a data-driven decision-making approach and increase data interoperability. When work orders are requested, information from service requests will be used by the system to collect required data from the common database (part 1), identify the issue, and prioritize maintenance tasks based on defined criteria. The maintenance schedule will then be generated. The maintenance manager can modify the schedule order generated and provide new input into the database (part 5). Based on the final schedule generated, the responsible crews will then be notified of the maintenance tasks assigned to them (part 2). Augmented/Mixed reality (AR/MR) glasses can be utilized to provide location of each task and relevant information required. Level of detail of information, structure and display format should be defined based on the asset type, nature of the task performed, and user preferences to reduce cognitive overload and enhance performance. Any missing information not provided to the user through the glasses can be retrieved by the user directly from the database using a built-in search and capture feature. The framework will be developed to learn and automatically capture changes to update the information provided in future tasks.

AR/MR glasses can be used to provide a step-by-step instruction based on the level of knowledge and expertise of the assigned crew to perform the maintenance task (part 3). Instructions can be provided using an application on the glasses or through remote collaboration with other users. Information provided through the glasses is accessed from the central common database (part 1).

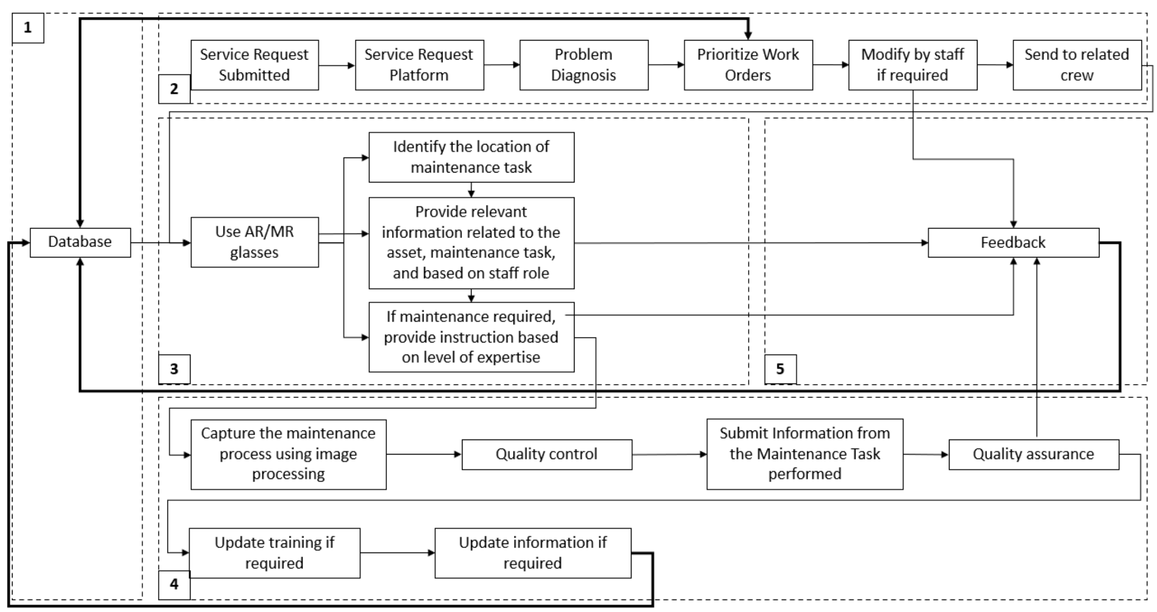

Figure 2.2. Framework for connecting the three challenge areas

While the AR/MR glasses provide access to needed information, they can also be used for QA/QC. If the guidance is provided to field staff using remote collaboration, users can receive feedback regarding their performance directly through their supervisor during and after the maintenance task is complete. If the guidance is provided through system instructions or videos, the glasses can use images processing to capture and analyze the user's gesture to provide feedback. Additionally, with the ability to record a maintenance session, recorded performance can be used for future quality check if needed. The proposed framework can address a more comprehensive QA/QC while reducing the time and staff required for performing the QA/QC. Feedback from QA/QC can be used to update training requirements, as well as instructions provided to field personnel to increase their performance (part 1 & 4). Information collected over time and through these processes can be used to support data-driven decision-making since the information are consistently and continuously collected and analyzed to find patterns and update the system accordingly. Additionally, such approach can avoid data duplication by using the data collected in one process for another process.

2.5 Conclusion

Due to the rapid improvements and affordability of technologies used for FM, more complicated and larger amount of data are created and are becoming more available to facility managers (Cao et al., 2014). The concept of big data can help with extracting meaningful and valuable information from the available data (Yang & Bayapu, 2019). Additionally, data analytics methodologies and machine learning algorithms can be used to process and investigate the collected data, find patterns, and drive conclusions to benefit the facilities and support their decision makings (Assaf et al., 2020).

The authors are planning to focus on the first area, processing work orders, moving forward with this research since this process involves a variety of factors and rankings. Therefore, implementing data-driven decision making and machine learning can assist with performing the process while supporting consistency in collecting and storing data. The authors are planning to conduct more semi structured interviews in addition to surveys to collect valuable knowledge to propose a solution for processing work orders. The solution will be validated using case studies and industry partners involved in facility maintenance.

Although many studies have highlighted the importance of consistency and interoperability in FM, the processes used in facilities are still lacking a proper connected framework and data management to support informed and data- driven decision making. This chapter provided an overview of prior research focused on three challenge areas and proposed a theoretical framework to address them. It is believed that the framework can enhance performance and quality of FM while reducing costs.

CHAPTER 3: CHALLENGES AND GAPS WITH USER LED DECISION-MAKING FOR PRIORITIZING MAINTENANCE WORK ORDERS[2]

3.1 Abstract

A vast amount of work orders is submitted daily which is a critical component of management for any facility. The process taken for prioritizing work orders, however, shows a high dependency on the extent of knowledge and experience of responsible staff available and is challenged by inconsistency in data collection, and uncertainty in decision-making. Making decisions and responding to a high number of requests demand intensive labor hours resulting in delays causing issues for facility managers. The high number of service requests, various work orders, and the required balance between cost and budget highlight the importance of the need for improving work order processing to optimize time and cost. Through review of the literature, unstructured and semi-structured interviews, this paper identifies various challenges and gaps in user-driven decision-making for processing work orders. The challenges identified include inconsistency in prioritizing orders, lack of data requirements and knowledge management, cognitive workload and biases, and inconsistency in data collection. Using data-driven decision-making methods can address existing challenges, improve the process of prioritizing work orders and enhance the quality of the work performed by timely responding to submitted requests. This will improve the operation and maintenance of facilities and increase occupants' satisfaction.

Keywords: Facility Management, Maintenance Work Orders, Prioritization, Strategic Decision-Making

3.2 Introduction

Facility management (FM) involves various functions including space management, communication, contract management, inspection, etc. (IFMA, n.d.; ISO 41011, 2017).

[2] This chapter has been submitted to an academic journal.

Among many of these FM functions, maintenance-related tasks occupy 79% of the facility managers' responsibilities (Besiktepe et al., 2020; Wang & Piao, 2019). A minor change in FM such as choosing the proper maintenance type, can greatly impact the cost, condition, and performance of the facility (Grussing & Liu, 2014; Kwon et al., 2020) which also addresses one of the main goals of FM, improving the economic life of buildings (Islam et al., 2019).

Work order processing is a big part of FM as large amounts of work orders are submitted daily. Different researchers have reported high number of service requests (e.g.,80,000 per year) in various facilities (Mo et al.,2017; Cao et al., 2015) which are good indicators of the high demand for maintenance requests as well as an indicator of the approaches taken by facilities to address the maintenance work orders (e.g., focusing on reactive maintenance rather than preventive maintenance). Both factors highlight the importance of improvement in managing and prioritizing maintenance work orders to save time and money while improving the performance of staff and the operation of the facilities (Ensafi & Thabet, 2021). Priority management is defined as the allocation of resources in a specific order to address operational productivity, customer service, and economic and strategic goals of the organization (Westbrook, 1994). Due to the high number of service requests, variety of work orders, and required balance between cost and budget, the allocation of resources to the maintenance tasks needs to be prioritized. Such an approach will optimize the use of resources and minimize the deterioration of the building with long-term considerations (Benitez et al., 2020; Chong et al., 2018).

This paper provides a review of the literature on work order processing and identifies existing challenges and gaps in user-driven approaches. It also discusses the impact of coping strategies resulting from cognitive workload as well as decision-making biases on the performance of facility staff. In order to explore existing practices in different facility types, identify data requirements and criteria used for processing work orders, and determine the challenges and gaps in each stage of work order processing, unstructured and semi-structured interviews were conducted with facility experts. The results of interviews are discussed in the results section. Finally, the paper concludes with suggestions on using data-driven approaches as opposed to user-driven approaches for addressing the issues identified.

3.3 Review of Literature for Work Order Processing

Although vast amounts of work orders are submitted daily (Mo et al., 2017), the process of prioritizing orders has been done manually or partially through management systems rendering the process very challenging. There are no current structured approaches for performing the prioritization process and every facility has its own strategy and approach (Lukens et al., 2019). In a traditional work order processing, work orders are requested by occupants or operation and maintenance (O&M) staff through phone calls, emails, or specialized systems and are received by the maintenance department (Mo et al., 2017). The staff will use their experience, knowledge, and judgment to analyze the work orders, prioritize the tasks based on specific criteria (e.g., cost), create schedules, and assign the tasks to qualified technicians (Bouabdallaoui et al., 2020; Cao et al., 2015; Roper & Payant, 2014).

An initial analysis of the literature using the VOSviewer (VOSviewer, n.d.) was conducted to identify most relevant papers from a pool of related papers. The VOSviewer analyzed abstracts and keywords and provided a list of high frequency words (Figure 3.1).

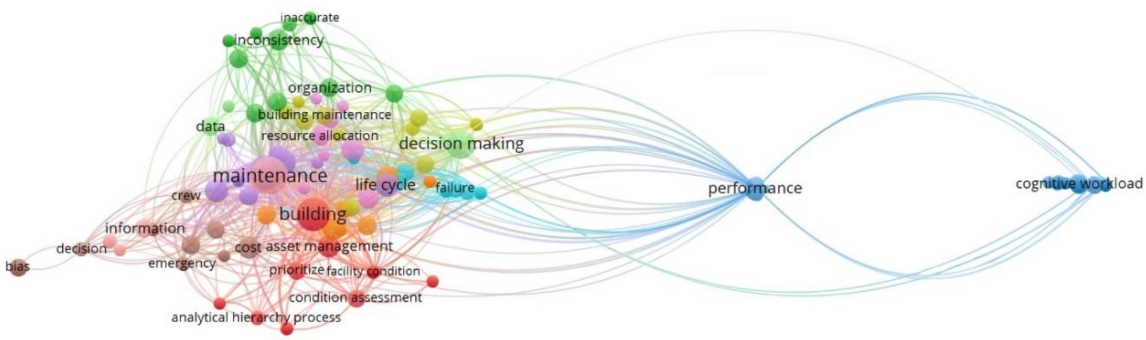

Figure 3.1. Keywords identified from literature review

The following subsections provide a summary of literature review addressing research conducted on work order processing grouped into three stages.

3.3.1 Data Requirements for Service Requests (Stage 1)

D'Orazio et al. (2022) implemented text mining into occupants' service requests to determine maintenance severity ranking and actions required. They also compared different sentiment analysis for prioritizing decisions. They first determined the dimensional differences between sentences and then evaluated the importance of specific words within the work order requests. Such approach allowed them to identify the work order category (e.g., electrical). They also used the sentiment analysis to understand the perception of the occupants about the failure event helping with priority analysis. However, due to the complexity of sentiment analysis, the recognition had limited ability to determine the level of request severity. Bouabdallaoui et al. (2020) implemented natural language processing for analyzing data associated with work requests, classifying the service requests, and assigning the tasks to the FM teams based on the nature of the issue (e.g., lighting). Their proposed approach had high prediction accuracy for some classes such as lighting and had lower accuracy for others such as electrical equipment. Defining data requirement may address inconsistency in data collection and processing (Yang & Ergan, 2017; Lavy et al., 2019) and reduce the complication of analyzing work order data. Besiktepe et al. (2019) explored historical work order data to determine frequent maintenance activities. They also investigated the relationship between the activities and building age and type. Based on their results, no relationship was identified. Their study highlights the importance of breaking down the maintenance activities to develop more effective condition assessment processes based on historical work order data. They also highlighted challenges with existing practices including lack of maintenance activity type capture and inconsistency in keywords of issue descriptions. Both challenges identified by the study can be addressed by defining comprehensive list of criteria and data requirements. Lavy et al. (2019) studied the use of Building Information Modeling (BIM) in reducing workorder processing time for buildings of a large university. Their results indicate that the benefits of using BIM over other management systems is not yet clear due to lack of standard rules and guidelines for capturing and storing data associated with work orders. Mo et al. (2017) implemented text mining into the data collected from service requests to develop a tool which can automatically predict the reaction type (emergency vs. routine) and necessary crew. They compared the performance and accuracy of three different algorithms. Developing requirements to provide more useful data when submitting a work order request may improve the performance of the tested models. Yang and Ergan (2017) focused on HVAC by exploring required information that should be stored in BIM to identify the cause of the problems and automate HVAC troubleshooting for different types of maintenances. The study is a good example of information requirements for storing relevant data to meet FM needs.

3.3.2 Analysis of Requests and Criteria for Work Order Prioritization (Stage 2)

Yoon et al. (2021) proposed a strategy to address the prioritization of deferred maintenances based on reliability determined from evaluating building, system, components, subsystem model, and total system evaluation. They believe that their proposed strategy can support budget allocation while diagnosing building conditions. Ali and Hegazy (2014) proposed a framework for prioritizing subsystems addressing the allocation of capital renewal funding in hospitals. They developed a priority index based on zones, systems, service quality, and performance of subsystems according to condition, level of service, sustainability, risk of failure, or combination of them. Poor facility performance is mainly due to cost constrains, lack of funding, budget cuts, and poor maintenance management (Besiktepe et al., 2020; Eweda et al., 2015); therefore, excluding budget and funding can negatively impact facility management.

Besiktepe et al. (2020) identified and ranked a set of general criteria for developing a multi criteria decision-making model to address lack of condition assessment practices, aging workforce, and resource allocation. Their study also highlights the differences between criteria ranking among public and private sectors and therefore, the authors recommended studying the criteria and their associated rankings for different types of facilities. Their study also highlighted the dependency on expert knowledge and aging workforce as existing challenges that require further consideration. The extent of knowledge and experience of the staff who analyze the service requests can influence the work order processing (Cao et al., 2015; Tam et al., 2017). Lack of knowledge about asset performance will lead to errors and asset failure, impacting the cost of O&M (Salem & Elwakil, 2018), causing extreme revenue loss every year (Bayasteh et al., 2019), and impacting occupants' safety and satisfaction (Cao et al., 2015). Furthermore, due to aging workforces, the individuals responsible for processing work orders retire. Consequently, their expertise and knowledge will leave with them and may not be transferred to their replacement individuals.

Lau et al. (2021) implemented a user-driven approach for evaluating the performance of sport facilities based on users’ preferences to determine the performance hierarchy of swimming pools. The result of their study reveals the importance of different services in relative to each other (e.g., building services vs. architectural aspects) which can support the priority of the resources and tasks that should be performed. Islam et al. (2019) explored the difficult building assets and elements to operate and maintain in addition to factors, assets, and elements which cause increased FM cost. Cost and difficulty of maintenance are two factors that may help with identifying the criticality of assets when prioritizing the work orders. Based on their findings, design errors, low maintenance quality, lack of maintenance plan and clear understanding of FM operation negatively impacted costs. Additionally, they selected roofs, construction joints, façades, HVAC, and sewer lines as difficult elements to operate and maintain. Wang and Piao (2019) used maintenance type and risk assessment in terms of reliability, maintainability, economy, and detectability to prioritize maintenance tasks for equipment components. Type of maintenance is one significant factor that can impact the criticality of an asset for prioritizing work orders, however, it is not necessarily considered when prioritizing work orders. Furthermore, considering the entire facility system as well as the association between different equipment for prioritizing the work orders was recommended by the authors for future research.

Eweda et al. (2015) created a hierarchy based on building type, space type, building categories, building systems, family type, and instance level (component properties) to develop a condition assessment model. Their study can be used towards selecting criteria for assigning criticality to the assets. Beauregard and Ayer (2019) explored the relationship between facility condition and academic outcomes for K-12 education. To enhance the facility condition, they prioritized work orders for routine maintenances based on four factors of influenced group, building status, building usage, and institutional enablers.

Considering comprehensive list of factors as well as major repairs such as emergency or critical breaks is critical for developing practical solutions.

Although different external factors may influence the process of prioritizing work orders such as the role of individuals in the facility, there are also internal factors that affect how individuals prioritize a set of request orders. Making decisions and responding to many requests demand intensive labor hours and are impacted by subjective judgments (Chong et al., 2019) and human errors such as underestimating an important criterion for processing work orders. Late responses can cause asset failure, which will negatively impact the environment, safety, and occupants' satisfaction (Bouabdallaoui et al., 2020; Mo et al., 2017; Salem & Elwakil, 2018).

Strategic decision-making requires individuals to select an optimal alternative from a set of available options. The alternatives often have various attributes complicating the decision-making process. Nevertheless, it is not possible or realistic to select one attribute for each alternative and based on psychological studies; humans cannot reliably compare multiple pairwise alternatives simultaneously due to information overload (Hollnagel & Woods, 2005). Consequently, overloading human operators with information negatively impacts their decision-making process (Dixit, 2018). Furthermore, insufficient information (missing or discarded information) can be challenging as it forces the operator to interpret and decide from a limited amount of information (Hollnagel & Woods, 2005). Availability of insufficient information (information underload) or excessive information (information overload) can impact cognitive workload leading to coping strategies (Table 3.1) to overcome and complete the assigned tasks (Hollnagel & Woods, 2005). Factors such as time restrictions or task complexity may also lead to coping strategies which are accelerated with insufficient information or data overload (Hollnagel 2011). As a result, high cognitive load can negatively impact working memory, performance efficiency, and executive functions (Mandrick et al., 2016; Galy et al., 2012). There is a need for reducing cognitive workload to allow operators and FM staff to focus on critical thinking by transferring their attention to knowledge intensive tasks rather than routine processes (Ensafi et al., 2021).

Table 3.1. Coping strategies for information overload/underload (Hollnagel & Woods, 2005)

Information overload/ underload	Strategy	Description
Overload	Omission	Temporary, arbitrary non-processing of information, some input is lost
Overload	Reduced precision	Trading precision for speed and time (shallower reasoning)
Overload	Queuing	Delaying response during high load on the assumption that it will be possible to catch up later
Overload	Filtering	Neglecting to process certain categories (non-processed information is lost)
Overload	Cutting categories	Reduce the level of discrimination; use fewer grades or categories to describe input
Overload	Decentralization	Distributing processing if possible
Overload	Escape	Abandoning the task; giving up completely
Underload	Extrapolation	Existing evidence is 'stretched' to fit a new situation
Underload	Frequency gambling	The frequency of occurrence of past events is used as a basis for recognition/selection
Underload	Similarity matching	The subjective similarity of past to present events is used as a basis for recognition/ selection
Underload	Trial-and-error (random selection)	Interpretations and/or selections do not follow any systematic principle
Underload	Laissez-faire	An independent strategy is given up in lieu of just doing what others do

Decision-makers may also be impacted by the different cognitive biases. These biases may impact their interpretation when making strategic decisions (Schwenk, 1985). Table 3.2 summarizes eight critical biases identified from analyzing relevant literature.

Table 3.2. Cognitive biases

Biases	Description	Reference
Prior Hypotheses / Judgements of Correlation and Causality	Being impacted by previous formed beliefs or hypotheses disregarding other evidence	Schwenk (1984) Barnes (1984)

Representativeness	Ignoring evidence reliability and having complications integrating different sources of information	Tversky & Kahneman (1974) Barnes (1984)
Focusing on Limited Targets	Ignoring other objectives/alternatives that are not appealing which is further impacted by the complexity of the environment	Das & Teng (1999) Schwenk (1984)
Exposure to limited Alternatives	Focusing and relying on limited number of alternatives that are based on incomplete information	Das & Teng (1999)
Insensitivity to Outcome Probabilities	Ignoring historical data and probability of previous events perceiving each problem as a unique problem	Das & Teng (1999)
Illusion of Manageability	Overestimating judgment and control due to overconfidence in managers	Barnes (1984) Das & Teng (1999)
Availability	Evaluating the frequency or probability of events based on the ease of recalling the event	Tversky & Kahneman (1974)
Adjustment and Anchoring	Depending on initial information and adjusting it to the situation leading to ignorance of other possible options	Tversky & Kahneman (1974)

3.3.3 Data Collection Following a Maintenance Task (Stage 3)

Ensafi and Thabet (2021) reviewed the existing challenges with FM maintenance practices and proposed a conceptual framework addressing the challenges. The framework includes a common database connecting different FM practices to support continuous data collection and interoperability. They highlighted the importance of defining data requirements to increase consistency in data collection and exchange through different maintenance practices. They also marked adjusting and updating systems as an important factor to provide practical solutions over time. Cao et al. (2014) developed an agent-based framework to prioritize work orders based on impact on comfort of occupants and energy consumption. Their research highlights the importance of response time on the satisfaction of the occupants and thus, a significant aspect to consider for addressing service requests. Furthermore, they highlighted the significance of understanding and capturing the root causes of maintenance problems and level of difficulties in addressing issues as they can greatly impact the repair time. Brundage et al. (2019) emphasized the need for and importance of updating and adjusting the FM systems with data as maintenance requires access to accurate asset information.

3.4 Methodology

This paper utilizes a qualitative research methodology to collect data about the existing practices for processing work orders, capture criteria used for prioritization, identify biases in strategic decision-making, and identify gaps and challenges in each stage of work order processing. The qualitative research approach comprises analysis of the literature and conducting unstructured and semi-structured interviews. The interview and questionnaire were conducted in accordance with the institutional review board (IRB) protocol IRB-21–731 submitted to IRB at Virginia Tech.

A non-random purposive sampling approach was used to recruit participants for the interviews to select individuals involved in processing work orders. Since the interviews included observations and based on the concept of saturation (Marshal et al., 2013; Mason, 2010), a total of seventeen participants, eleven males and six females, were recruited through professional connections of the authors or recommended by individuals working in facilities. The interviewees were contacted between September 2020 and March 2022 through email. All interviews were conducted through video conferencing, and each took about an hour. The qualitative research methodology was conducted using the following five steps:

Step 1: The literature reviewed was analyzed to identify the criteria used as well as gaps and challenges determined in previous studies conducted.

Step 2: This step involved two unstructured interviews with two facility managers from two academic institutions. The format was a general open discussion involving unstructured questions and focused on discussing the process of prioritizing work orders and creating schedules. The interviewees were asked to describe their practices in terms of processing work orders, discuss the challenges they face, and provide possible suggestions for enhancing the process.

Step 3: The information from the unstructured interviews were analyzed and used in combination with the literature review to prepare a set of questions (Table 3.5) for conducting semi-structured interviews.

Step 4: This step involved conducting 15 semi-structured interviews. The tasks involved in each stage of processing work orders were discussed with participants from different facility sectors including higher education, commercial, healthcare, government, and a software company (Figure 3.2). This allowed including a wide range of perspectives while covering various practices taken for processing work orders. As part of the semi-structured interview, participants were asked to prioritize a set of work orders and describe their logic and approach in processing them to identify possible limitations. The work orders included examples of work orders received from an academic facility. This allowed to observe how the participants process work orders and capture best practices they use to reach a prioritized list

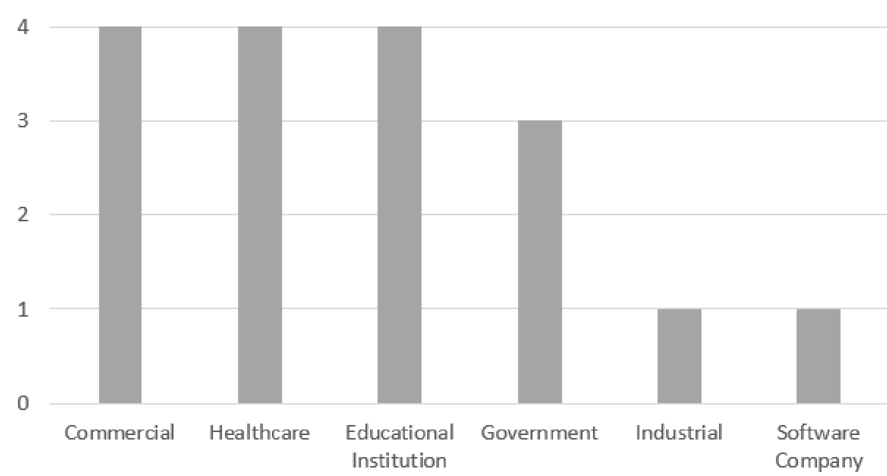

Figure 3.2. Facility types

Step 5: The information collected from the semi-structured interviews was analyzed using a deductive qualitative coding approach. Results identified were categorized based on the stages of work order processing.

There are different perspectives on the reliability and validity of data collected through qualitative studies. While some researchers believe that reliability requires measurements and is not related to qualitative studies, others have suggested using trustworthiness, credibility, neutrality, and consistency instead of reliability and validity (Golafshani, 2003). Noble and Smith (2015) suggested the following strategies for addressing the trustworthiness and credibility of qualitative studies: a) acknowledging personal biases as well as biases in sampling, data collection, and analysis; b) considering and including different and similar perspectives; c) clear description of the process; d) sharing and discussing the interview questions and process with other researchers; e) data triangulation; f) collecting details of the context

To address reliability and validity of the interviews, the researchers took the following steps. First, the researchers selected individuals based on their roles in the facilities to include participants involved in processing work orders. Second, semi-structured interviews increased data collection consistency since the questions were almost the same across all interviews. Third, recruiting participants from five different facility types allowed including a broader range of perspectives. Fourth, the process taken for sampling, data collection, and analysis is described in detail. Fifth, the questions developed for interviews were discussed with other researchers as well as a FM expert to ensure their practicality.

3.5 Analysis and Results

3.5.1 Literature Analysis

Based on the analysis of literature reviewed, the gaps and challenges in processing work orders (Table 3.3) were identified and the list of criteria (Table 3.4) considered by previous studies was determined.

Table 3.3. Challenges and Gaps

Challenges and Gaps	Reference	Stage1	Stage2	Stage3
Classified hierarchy to capture system/components for the requests	Bouabdallaoui et al. (2020)	x		
Cognitive overload impacting the user’s performance	Galy et al. (2012)		x	

Considering organizational needs when identifying and prioritizing the list of influential criteria	Besiktepe et al. (2020) Chong et al. (2019) Yang et al. (2018)		x	
Considering the entire facility system as well as the association between different equipment	Wang & Piao (2019)		x	
Considering the source of funding and funding mechanism	Sadeghi et al. (2018) Ali & Hegazy (2014)		x	
Criteria selection and ranking based on facility type	Besiktepe et al. (2020)		x	
Decision-makers may be impacted by different cognitive biases	Schwenk (1985)		x	
Delays in processing leading to asset failure and downtimes	Hong et al. (2020) Salem & Elwakil (2018)		x	
Dependency of work order processing on staff experiences and extent of knowledge	Cao et al. (2015) Tam et al. (2017)		x	
Discontinuous data collection	Ensafi & Thabet (2021)			x
Excluding budget	Besiktepe et al. (2020)		x	
Excluding different types of maintenance	Chen et al. (2018) Beauregard & Ayer (2019)		x	
Focusing on single maintenance tasks/work crew	Chen et al. (2018)		x	
Generalizing one solution to different types of facilities	Besiktepe et al. (2020) Chong et al. (2019)	x	x	x
Identifying assets that are difficult to maintain	Islam et al. (2019)		x	x
Inconsistency in data input and structure	Yang & Bayapu (2019) Lukens et al. (2019)	x		x
Interoperability issues	Yang & Bayapu (2019)	x	x	x
Lack of comprehensive list of factors	Beauregard & Ayer (2019)		x	
Lack of defined (Unclear) organizational priorities and goals to remove subjective judgements	Chong et al. (2019)	x	x	x
Lack of information requirements	Yang & Ergan (2017) Lavy et al. (2019) Lukens et al. (2019)	x	x	x

Multiple data entry/ data duplication	Chekryzhov et al. (2018)	x		x
Need for a common database	Ensafi & Thabet (2021) Farghaly et al. (2018)	x	x	x
Not considering major repairs such as emergency or critical breaks	Beauregard & Ayer (2019)		x	
Number of staff available for processing WOs	Beauregard & Ayer (2019)		x	
Overlooking Client/occupant/owner's satisfaction	Mo et al. (2017) Cao et al. (2015)		x	
Understanding and capturing the root causes of maintenance problems	Cao et al. (2014)			x
Understanding and identifying costly assets	Islam et al. (2019)		x	x
Update and adjust the system/ software used through the building lifecycle	Brundage et al. (2019) Martínez-Rojas et al. (2016)	x	x	x
Update information through the building lifecycle	Volk et al. (2014)	x	x	x

Table 3.4. List of criteria

Criteria	Reference
Aesthetic	Smith & Stewart (2007)
Budget	Besiktepe et al. (2020)
Building age	Besiktepe et al. (2019)
Building/space type	Beauregard & Ayer (2019) Eweda et al. (2015)
Codes and regulations	Besiktepe et al. (2020)
Cost of maintenance	Selim et al. (2016)
Energy usage	Cao et al. (2015)
Emergency level	Chen et al. (2018)
Historical\cultural value	Dann et al. (2006)
Influenced group	Beauregard & Ayer (2019)
Level of risk	Wang & Piao (2019)
Maintenance duration	Besiktepe et al. (2020)
Occupants' preferences\satisfaction	Cao et al. (2015) Lau et al. (2021)
Optimal distance	Chen et al. (2018)
Problem type	Bouabdallaoui et al. (2020) Chen et al. (2018)
Remaining life cycle	Bayesteh et al. (2019)

Safety	Salem & Elwakil (2018)
Severity of failure/emergency	Chen et al. (2018)
Source of funding	Sadeghi et al. (2018)
Sustainability	Ali and Hegazy (2014)
Systems/ Subsystem	Yoon et al. (2021) Eweda et al. (2015) Ali & Hegazy (2014)
Type of building/space	Beauregard & Ayer (2019) Eweda et al. (2015)
Type of maintenance	Wang & Piao (2019)
Zone	Ali & Hegazy (2014)

3.5.2 Interview Questions

Based on the unstructured interviews conducted, a set of questions (Table 3.5) was prepared addressing practices at the different stages of work order processing. The questions were focused on identifying the criteria and gaps and challenges in the three stages. The developed questions were intended to facilitate the semi-structured interviews discussed in the next step.

Table 3.5. Questions developed for semi-structured interviews

Questions	Background Information	Stage1	Stage2	Stage3
What is the type and size of your organization?	x			
What types of maintenance do you consider?			x	
What types of maintenance do you consider? When do you identify the type of maintenance in your process? Are there different processes for different types of maintenance? How is the individual(s) responsible for processing and prioritizing work orders selected? How do you manage the emergency work orders? How often do you prioritize the work orders? What criteria do you use for prioritizing work orders?			x	

Please prioritize the list of work orders provided and describe your logic. Based on the definitions of biases and coping strategies, could you provide examples in maintenance work order processing?				
Do you collect information following the completion of the maintenance task? What information do you collect?				x
Do you use any specific system for receiving and/or processing work orders? What is the workflow for processing work orders in your facility?		x	x	
How is the process of prioritizing work orders and its associated information updated? What are some of the challenges in your practices that require further consideration? What suggestion do you have for enhancing this process?		x	x	x

3.5.3 Analysis of Semi-Structured Interviews

Following interviews with industry experts, a qualitative data analysis was conducted to identify similarities, differences, and challenges and gaps among existing practices. A proper data analysis should consider both the details and the big picture at the same time. Analysis of the information captured from the interviews was completed in the following two steps.

Step-1: A narrative analysis was conducted following data collection from each interview to understand the existing practices, the criteria used for prioritizing work orders, data requirements, and the challenges and gaps with existing processes.

Step-2: A deductive qualitative coding approach (Table 3.6) was selected to categorize the data collected from the interviews based on personal interpretations. Coding and classification of data have been highlighted as the most common procedure for analyzing data collected from qualitative studies (Habib et al., 2012). Coding can be used to assign texts to a category allowing researchers to continuously compare the information, identify the similarities, differences, and patterns within the data collected, and determine their relationship with the research questions (Belotto, 2018; Habib et al., 2012; Trochim & Donnelly, 2001).

Table 3.6. Examples of qualitative coding approach

Statement	Code	Definition
"Their knowledge about the campus and all the buildings is important. They are usually selected from the staff who do the building assessments since they have the knowledge and experience."	Staff selection based on experience	Staff are selected based on experience
"The administrator supervisor processes the work orders, and he/she might be trained or not."	Training staff	Staff may or may not be trained for performing the task
"We collect the date, subject, description, assigned to, action dates, and when it was closed"	Data requirement for service requests	The facility has data requirements for receiving service requests
"We only collected the description of the issues in a text format"	No data requirement for service requests	The facility doesn't have data requirements for receiving service requests
"We process and prioritize all types of work orders together"	Work order prioritization at top level	Tasks are assigned to the maintenance crews after prioritizing the work orders
"The work order is assigned to a group then the people in the group will prioritize them"	Work order prioritization at shop level	Work orders are assigned to the related crew to be prioritized at the shop level

3.5.4 Summary of Existing Practices

From the interviews, it was realized that while some facilities required specific inputs from the individuals requesting work orders, other facilities only collected a description of the issue in text format. Common factors collected from the service requests included: requestors' information and their contact number, date, building name/number, location/room, and request/issue. Other factors considered by different facility managers included: type of requests, system/asset type, occupant, category, desired date, excluded dates, action dates, any specific asset/equipment if it is known, a budget code/ financial source, and safety.

In terms of software used for receiving and processing work orders, operators of large facilities tend to use an integrated workplace management system (IWMS) or commercial FM software such as AiM by AssetWorks while others used in-house proprietary software to create a more customized solution. Some facilities used their system for capturing, processing, and scheduling work orders (e.g., preventive maintenances) while others used the system only for capturing information.

Almost all participants indicated that they selected the responsible person for prioritizing work orders based on their experience, knowledge of the facility, and familiarity with the shops. While they highlighted the possibility of training, only three indicated that they provide training for preparing individuals for this role. One of the participants also highlighted the significance of staff understanding in terms of how to use FM system to its optimum capabilities. The number of individuals involved in processing work orders varied based on facility size.

Considering the type of work orders, some received all types of work orders and processed them all together while others had different procedures and, in some cases, had specific crews for different types of work orders. For instance, one institutional facility manager used a numeric system for prioritizing preventive maintenance tasks by assigning “criticality factor” to assets indicating the importance level of that asset in relative to other assets. However, their reactive/corrective maintenance tasks were processed manually and independently from preventive maintenance tasks. Participants from other facilities used a “criticality number” as time limit indicator for responding to work orders requested. For instance, a higher priority number indicated that the facility had 8 hours to respond to the work order, while a lower number allowed for a 30-day limit to respond. Additionally, not all facilities considered all types of maintenance. For those facilities which had different maintenance types, the type was selected based on manufacturer recommendations, inspections, required testing, or regulatory requirements. Few facilities were still in the infancy stages for implementing all types of maintenance including predictive maintenance.

In terms of prioritizing the work orders, some facilities added the work order to the queue as they were received by the facility office while for others, work orders were processed daily or weekly (excluding emergency requests). Considering the level in which work orders were prioritized; some facilities assigned the maintenance tasks to crews after prioritizing the full list of work orders. In other words, work order prioritizations were done at the first level. Other facilities broke down their work orders into specific categories (such as mechanical, electrical) and assigned work orders under each category to the respective crew, which in turn performed their prioritizations at the shop level.

The common criteria identified from the interviews included due date, emergency level, safety, codes and regulations, location, cost, budget, space type, and failure frequency. The specific criteria used by the facilities included: area served, count of an asset, impact on the function of the space, building age, scope of work, funding, time of the request, deadline for the customer, zones, parts availability, role of the requestor, occupant type, energy usage/sustainability factors, cosmetic, maintenance duration, type of maintenance, crew availability, the severity of the failure, maintenance difficulty, and warranty.

Although not all facilities collected data after performing the maintenance tasks, the following data were collected by some of the facilities: completion date, rate of completion, charge time and any parts purchase/taken from warehouse, cost of resources, number of tasks completed by the individual, difficulty with repair (e.g., access issue), and task duration.

3.5.5 Identified Gaps and Challenges

Based on the information collected from the interviews, various challenges and gaps at different stages of work order processing were identified. The following section provides details of these gaps and challenges.

Collecting enough information from a submitted service request to identify the possible issue was marked as one of the existing challenges. Not all facilities had a system dedicated to receiving work orders. In some cases, there were limited access to the system meaning that only facility staff could submit the work orders through the system while occupants had to submit their work orders through phone calls or emails. In cases which the facilities had systems for receiving work requests from everyone, most of the participants indicated that they still received requests through phone calls, emails, or even walk ups which made it difficult for them to capture a record of the issues that occurred. On the other hand, receiving requests through the facility system had its own challenges. In cases when the only input provided by the requestors was the description of the issue in textual format, staff had challenges with identifying the issue as descriptions were short, insufficient, and unclear. In cases where facilities requested specific information about the work orders submitted (e.g., location, possible system involved), the requestors were not necessarily required to fill out all the information requested. Furthermore, there were no documented standard to help facilities in determining information requirements for capturing requests that could support work order processing. Such approaches increased the time for processing work orders since in some cases, they had to contact the requestors a few times to receive details, identify the issue, and plan accordingly. Delayed responses could also lead to asset failures and increased cost of operation.

Although preventive and predictive maintenances can positively impact the FM and the quality of their services, not all facilities considered these types of maintenances. Furthermore, while some facilities used their management system to process or schedule specific types of work orders such as preventive maintenance, other facilities used the system only for capturing information. The processing and prioritization of work orders in such facilities were still done by facility staff or shops.

The list of criteria used for prioritizing work orders and their associated rankings were not consistent nor comprehensive. The criteria were selected by the person performing the task and therefore, the logic and knowledge behind the prioritization were not captured and were not used by others. Lack of requirements for determining the list of criteria and their associated ranking increased the inconsistency as individuals could select different sets of criteria or different ranking orders each time they had to process a list of work orders. Furthermore, inconsistency in processing and prioritizing work order existed among staff within the same facility impacting the final schedule. Some facilities did not consider prioritization and they addressed their work order tasks in the order that they were received unless they were emergency requests or involved high-value assets.

After ranking a list of criteria, interviewees were asked to rank a list of work orders given to them during the interview. It was realized that some of the factors they used were not included in the list of criteria that they initially provided for prioritizing work orders. These factors included: distance from shops, the magnitude of the issue (e.g., amount of leakage), parts availability, type of maintenance since different crews were responsible for different types of maintenance, task duration, count of an asset (e.g., one generator vs. few generators), and the number of occupants in the space impacted by the maintenance task. In some cases, the ranking of work orders by participants differed from the original ranking response they provided when presented by the set of questions. For example, the distance to maintenance location was given a low priority by participants when responding to questions asked early in the interview but received a higher priority when participants ranked the sample work orders provided. Such inconsistencies proved the importance of capturing knowledge and best practices from experts while they actually perform their tasks.

Participants also emphasized that due to the large amount of work orders submitted daily, staff could be impacted by cognitive workload or biases (Table 3.7) negatively affecting their processing ability and performance. As a result, individuals might avoid, underestimate, or miss using a significant criterion for processing work orders.

Table 3.7. Example of cognitive biases and coping strategies in work order processing

Bias/coping strategy	Example
Similarity matching	Assuming that the problem is same as the issue that was raised previously for similar assets produced by the same manufacturer.
Extrapolation	There were issues with automatic locks in building xx as well, so we assumed it was related to electricity interruptions.
Filtering	Many false alarms occurred previously in the same location leading to ignorance for new ones. Because of the budget cuts & limited resources certain steps in the condition assessment might be neglected.
Exposure to limited Alternatives	Decision on the material/technique with a limited number of quotes: Ex: Lighting fixture change decision from conventional to LED with the quote of one manufacturer or with the energy performance data with one or limited number of manufacturers.

Queuing	Small tasks such as light bulb change, or a minor plumbing issue can be neglected during the high load. Mostly it ends up with more significant issues such as safety.
Prior Hypotheses / Judgements of Correlation and Causality	Not considering other indicators. For example, occupants don't know how to manage the system and the system is working perfectly.

It was also realized that data was not collected consistently and continuously through all stages of work order processing including following the completion of maintenance tasks. Although some facilities collected such data (e.g., rate of completion), other facilities did not require it missing on the opportunity to benefit from data collected that could inform and aid in future decision-making. For example, capturing detailed data after completing a work task for a hot water pump being repaired or maintained, such as number of hours spent on the task and the number of field staff involved, can greatly help with processing similar future work orders. From the interviews, it was realized that such information was not collected by many facilities or was collected with very little detail. Due to lack of formal guidelines specifying what to collect and how the data should be captured, data collected was sometimes irrelevant and did not necessarily address the needs of processing and prioritizing similar future work orders. Understanding the overlap between data collected following the maintenance tasks and data used for processing work orders can assist with developing requirements to collect comprehensive and consistent information to support future work order processing.

In general, data quality and data structure within the facility systems were marked as the main challenges they faced. Additionally, there was a lack of connectivity between different systems (e.g., finance, diagnostic) used by the facility as well as different stages of processing work orders hindering the possibility of benefiting from the data collected. Not considering the big picture and the association between the different stages restricted the development of requirement guidelines for data to be captured. This led to inconsistency in data collection and processing among different individuals and facilities.

3.6 Discussion

In this paper, the authors identified and highlighted the current best practices for processing work orders as well as the challenges and gaps associated with performing this critical task.

This was accomplished through review of the literature and using unstructured and semi-structured interviews. Exploring different types of facilities and practices allowed the authors to identify similar and diverse challenges in processing work orders. Investigating different stages of work order processing also allowed for identifying challenges associated with each stage and with better understanding of connectivity and data requirements overlap between all the stages. This can lead to a consistent and continuous data collection to improve on current best practices.

Results from literature reviews and interviews indicated that there was inconsistency in data input and structure as well as a lack of interoperability and connectivity between different systems used by the facilities. Additionally, lack of information requirement as well as a demand for updating and adjusting the facility system and information through the building lifecycle were highlighted by both literature and interviews. Lastly, both sources marked the importance of capturing the root causes of maintenance problems for addressing future work orders.

Although previous studies had defined a classified hierarchy to be able to capture the system and component associated with a request, the interviews highlighted the positive impact of such classification only if the hierarchy is the same across all the buildings managed by the same facility. While previous studies had highlighted the importance of determining organizational goals for identifying and prioritizing a list of criteria for processing work orders, the interviewees focused on their organizations' best practices. For example, few studies used the asset system type as a criterion because they considered prioritizing all work orders together. However, results from interviews showed that some facilities sent the work orders to the related shop asking them to prioritize the orders within their own department. Considering different practices impacts the development of information requirements.

Most of the studies included in the literature were focused on one stage of work order processing. In order to develop practical solutions and define data requirement, facilities need to consider the big picture and study the data overlap between different stages as determined during the interviews. For example, maintenance duration was selected as a criterion by the participants for prioritizing work orders. This information should be collected following the maintenance tasks to support future work order processing.

The interviews showed that criteria selection and ranking varied among individuals and facility types. However, to investigate the actual impact of facility type on criteria selection as suggested by the literature, more data needs to be collected. While the focus of previous studies was on selecting criteria by subjective input, interviews highlighted the possible differences in criteria selection and ranking when performed in context. This can be counted as a positive impact as studying the existing practices will provide the actual list of criteria used as well as their ranking. However, it is also important to consider the impact of other factors such as cognitive biases and coping strategies when following such approach. Most of the studies included in the literature review focused on few criteria while there are more criteria considered in practice depending on the experience and knowledge of the individuals performing the task. While previous studies highlighted the dependency of work order processing on staff experiences and knowledge, the interviews presented the use of a priority number for specific maintenance types or assets in some facilities. Addressing the association between different systems and assets was recommended by the literature and was confirmed to be a criterion used in actual practices from the interviews. While an asset might not have a high priority itself, its impact on another high priority asset or system can increase the priority of the work order for the low priority asset. Different studies considered the source of funding and occupant satisfaction as criteria for processing work orders. The interviews indicated that the consideration of source of funding depended on the type of maintenance or on the asset(s) being addressed. Additionally, the importance of occupant satisfaction depended on the type of facility as well as the role of the occupant.

While the review of literature provided background information on cognitive biases, cognitive workload, and coping strategies during strategic decision-making, the results of the interviews presented examples of biases and coping strategies in processing work orders. Identifying possible coping strategies and cognitive biases in work order processing can help with addressing some of the existing challenges such as defining data requirement and providing a list of criteria.

Based on the results of interviews, additional criteria were identified that were not listed in previous studies. These criteria included area served, count of an asset, association between different equipment or systems, availability of staff to perform the task, availability of resources, distance from shops, end date, indoor environmental quality, maintenance difficulty, number of occupants in the space, role of the requestor, magnitude of the issue, time of the request, and warranty. This highlights the importance of using mixed methods for identifying more comprehensive list of criteria and their ranking for processing work orders as well as for developing data requirements to increase the consistency within existing practices.

This study had the following limitations. First, non-random sampling approach was selected over random sampling due to complications of recruiting participants that were involved in work order processing, Second, the interviews were conducted over an extended time (approximately 1.5 years). Third, responses from other facility types such as residential, hospitality, or mix-used were not included in this study as the authors were not able to recruit participants from those facilities.

3.7 Conclusion

Based on the literature review and interviews conducted, existing practices have challenges associated with lack of data requirements, inconsistency, variability across individuals' criteria selection and decision-making approaches, and discontinuous data collection in different stages of work order processing hindering the opportunity to benefit from data collected. It is concluded that prioritization of maintenance work orders is impacted by individual judgments, biases, and coping strategies resulting from cognitive workload. According to the challenges identified, the following points are suggested by the authors to enhance the existing practices.

1. Understanding the data overlap between different stages of work order processing
2. Developing data requirements to support consistency and accuracy
3. Determining a comprehensive list of criteria and their associated rankings for prioritizing work orders to support consistency

4. Enforcing continuous data collection to be able to benefit from data collected following the completion of maintenance tasks and draw insights for enhancing existing practices
5. Implementing data-driven decision-making methods, as opposed to user-driven, to minimize biases and coping strategies while increasing consistency and accuracy
6. Developing a flexible system to allow consistent development and update of information and system over time to provide practical solutions

Defining information requirements as well as benefiting from data-driven decision-making can have multiple benefits including

1. Decreased cognitive workload allowing FM staff to focus and respond to unique situations and anomalies
2. Time reduction between decision-making and execution
3. Consideration of multiple criteria and attributes supporting accuracy
4. Recording the processes for identifying gaps and adjusting the processes accordingly
5. Fewer asset failures and downtimes leading to reduced cost, higher performance, and increased customer satisfaction
6. Reduce challenges faced by newly hired FM staff by capturing previous processes and providing requirements

In this paper, the authors studied the challenges and gaps with existing practices for processing maintenance work orders through literature review and interviews. A larger size pool of participants is needed to continue to study the impact of facility type, facility size, and years of experience on work order processing. Additionally, collecting data from a broader range of participants with diverse experience maintaining diverse facility types will allow the authors to determine a more comprehensive list of criteria and their ranking for prioritizing work orders.

It should be noted that a follow up study is currently being conducted using survey questionnaires to collect data from a bigger pool of individuals covering a wider range of perspectives and practices. This study is targeting the implementation of data-driven decision-making methods.

CHAPTER 4: INVESTIGATIION OF WORK ORDER PROCESSING IN DIFFERENT FACILITIES: A QUESTIONNAIRE-BASED SURVEY[3]

4.1 Abstract

Processing and prioritizing work orders constitute an important part of facility management given the large amount of work orders submitted daily. User-driven approaches are currently more prevalent for processing and prioritizing work orders but have challenges including inconsistency and subjectivity. Data-driven approaches can provide an advantage over user-driven ones in work-order processing; however, specific data requirements need to be identified to collect and process the functional data needed while achieving more consistent and accurate results. Considering these, this chapter presents the findings of an online survey conducted with facility management experts who are directly or indirectly involved in processing work orders in building maintenance. The findings reflect the current practices of 71 survey participants on data requirements, criteria selection, rankings, with current shortcomings and challenges in prioritizing work orders. In addition, differences between criteria and their ranking within participants' experience, facility types and facility sizes are investigated. To address the inconsistency and subjectivity in the process of prioritizing work orders and to demonstrate the benefit of using decision-making methods in FM practices, analytical hierarchy process (AHP) was utilized. The findings of the study provide a snapshot of the current practice in facility management work order processing which aids with developing a comprehensive framework to support data-driven decision-making and address the challenges with user-driven approaches.

Keywords: Facility Management, Work Orders, Prioritization, Building Maintenance, Analytical Hierarchy Process

[3] This chapter has been submitted to an academic journal.

4.2 Introduction

The ISO 41011:2017 Facility Management-Vocabulary standard defines Facility Management (FM) as an "organizational function which integrates people, place and process within the built environment with the purpose of improving the quality of life of people and the productivity of the core business" (ISO 41011, 2017, p.2). FM integrates management practices with technical knowledge to plan, provide, and manage productive and effective built environment (Chanter & Swallow, 2008) with three main goals: (i) increasing productivity, (ii) minimizing cost, and (iii) providing/accessing information supporting strategic planning (Teicholz & Techolz, 2001).

Based on previous studies, FM practices constitute 60% of the building costs in its entire lifecycle (Guillen et al., 2016). In addition, a high percentage of maintenance costs in the FM practices with over 65% was reported in several studies. (Chen et al., 2018; Sadeghi et al., 2018; Thabet & Lucas, 2017). Building maintenance is a combination of actions performed to retain, restore, and improve facilities to perform its required functions with the desired output (Wood, 2009). Thus, operation and maintenance (O&M) practices generate a large amount of data requiring facility managers to develop plans for capturing, storing, and analyzing the data to support the organization's goal (IFMA, 2021). Collecting, processing, and managing such amount of data is a key challenge in maintenance management (Chanter & Swallow, 2008) which may lead to poor facility performance when planned ineffectively. (Besiktepe et al., 2020).

Prioritizing and processing work orders comprise a significant part of FM practices that generates a large amount of information with hundreds of orders in daily operations (Mo et al., 2017). Generic examples of building maintenance work orders including common categories of each order are presented in Table 4.1. User-driven approaches including manual work are currently more prevalent in processing and prioritizing work orders. Therefore, overcoming the challenges in managing work orders manually requires a team of specialized and experienced facility staff to perform it efficiently. Even though it is prevalent, manually processing work orders bring additional challenges in FM practices that mainly include lack of consistency (Lukens et al., 2019) and subjectivity (Bouabdallaoui et al., 2020; Cao et al., 2015). In order to propose solutions addressing these challenges, more applied studies are required to reveal the industry practices, determine the gaps and challenges., and identify best practices.

Table 4.1. Example of work orders

Work Order Number	Date Needed	Type of Order	Description	Location
109450	2022-02-10	Preventive	Annual service of fume hood exhaust fan	Building A, Room number 123
109451	2022-02-8	Corrective	No power to hot water pump	Building C
109452	2022-02-5	Emergency	Elevator in front of lobby is not working	Building C
109453	2022-02-8	Corrective	Men’s restroom faucet is leaking	Building B, First floor

In light of these, this chapter provides a brief background on challenges and gaps in existing practice for processing maintenance work orders based on literature review and interviews conducted in prior chapters (chapter 2 & chapter 3). Additionally, an overview of data-driven and decision-making approaches used for prioritizing a set of alternatives including work orders are presented as they can be used to enhance consistency. The chapter presents the findings of an online survey conducted with facility management experts who are directly or indirectly involved in processing work orders in building maintenance. The findings reflect the current practices of 71 survey participants on data requirements, criteria selection, rankings, with current shortcomings and challenges in prioritizing work orders. In addition, differences between criteria and their ranking within participants’ experience, facility types and facility sizes are investigated. Identifying and determining the criteria and their rankings in the FM practices are essential for helping professionals in their decision-making and strategic planning processes (Yoon et al., 2021; Besiktepe et al., 2020; Beauregard & Ayer, 2019). To address the inconsistency and subjectivity in the process of prioritizing work orders and to demonstrate a practical tool to FM professionals in work order processing, analytical hierarchy process (AHP) was utilized. The section concludes with describing the challenges associated with implementing such methods. The chapter concludes with recommending the implementation of a more automated approach to address the challenges with user-driven methods. FM requires an approach in which there is access to accurate and reliable information about buildings systems as well as building components (Sadeghi et al., 2018). Information requirements should be defined in different levels of strategic planning, management, and operations to properly address O&M challenges (Chanter & Swallow, 2008). The findings of the study provide a snapshot of the current practices in FM work order processing which aids developing a comprehensive framework to support data-driven decision-making and address the challenges with user-driven approaches.

4.3 Work Order Prioritization

Every facility receives multiple work orders daily, with different severity and criticality levels. It is crucial to assess and prioritize the maintenance tasks as inefficient prioritization can lead to additional cost of materials and labor work (e.g., assigning a routine task to an expert technician) or equipment failure. Studies have presented 50 billion dollars cost due to unplanned downtimes in manufacturing industry (IndustryWeek and Emerson, n.d.). Furthermore, lack of proper prioritization can lead to work order backlog and deferred maintenance which may result in significant costs as opposed to regular and preventive maintenance (Gocodes, n.d.). Priority management is the allocation of resources in a specific order to respond to operational pressure or customer service supporting the economic and strategic goals of the organization (Westbrook, 1994). Considering the complexity of these processes, standardization of data captured and definitions of maintenance tasks for creating, planning, scheduling, and executing maintenance work orders are critical. Having access to proper and required data with critical factors and criteria in work order processing will help with providing a clear and standard approach supporting the organizational goals in FM practices (Lukens et al., 2019).

4.3.1 Background

A current study (chapter 3) identified that most facilities have not developed specific data requirements for maintenance work orders, identified issues, and information collected following maintenance task performance. As a common practice, processing work orders through phone calls and e-mails is prone to errors and inconsistency as the result of different levels of experience and knowledge, as well as judgment and biases of staff

(Bouabdallaoui et al., 2020; Cao et al., 2015, Schwenk, 1985). Paper-based information are still used for transferring information, although maintenance systems such as computerized maintenance management systems (CMMS) and computerized aided facility management systems (CAFM) are available (Cheng et al., 2020). On the other hand, while some facilities are using maintenance management software, the data requirements have not been explored and determined in detail. Therefore, required data are not comprehensively collected and the collected data cannot be utilized effectively in the process. Additionally, there is a need to define requirements related to the information format of data entered into the systems. Facilities collect information in textual and descriptive format which makes it more difficult and complicated to benefit from data-driven decision-making.

Moreover, the criteria used by different individuals in the same facility are not consistent as there are no specified requirements for necessary criteria for prioritizing maintenance work orders and their importance. Facility management staff highly utilize their knowledge, experience, and familiarity with the facility to process and prioritize work orders. This common practice highlights the issue with the impact of experience, level of knowledge, and biases (Tam et al., 2017; Barnes, 1984). Additionally, processing large amounts of maintenance work orders can lead to cognitive workload negatively impacting the performance of facility staff (Hollnagel & Woods, 2005). Studies have highlighted operator error and lack of time for maintenance as main reasons for unscheduled equipment downtimes (FinancesOnline, 2022). Delays in processing caused by cognitive workload, decision-making biases, lack of knowledge or experience, poor judgment, and staff unavailability can lead to asset failure or downtimes negatively affecting the cost of operation and maintenance while reducing the safety and satisfaction of occupants (Beauregard & Ayer, 2019; Hong et al., 2020; Salem & Elwakil, 2018). A study conducted by Chan et al. (2021) has marked unplanned equipment breakdowns as top five challenges faced by facilities.

To address some of the challenges in existing practices, some studies or facilities have considered assigning a priority number such as 1 for immediate concerns and 3 for long-term concerns to assets to determine their relative importance (Teicholz & Techolz, 2001). However, based on the interview results from the prior study described in chapter 3, the criticality number assigned to assets is not robust and may differ from daily practices when assigned outside of the context/maintenance situation. Another issue with existing systems is that they are not updated and adjusted over time to provide a practical solution for FM practices.

Lack of data requirement created challenges with capturing data as well. In order to benefit from the data collected, data should be captured consistently and continuously. However, many facilities have not defined a requirement to determine what information should be collected after the maintenance tasks are performed such as start and finish time, number of maintenance staff who performed the task, and equipment tag or identification. Such approach leads to discontinuous data collection hindering the efficient use of the data collected. Also, in cases where facility staff collect information, the information collected do not include details that would benefit and guide future maintenance work orders.

All the factors mentioned above highlight the significance of proper maintenance work order management to improve the facilities' performance (Ensafi & Thabet, 2021). Furthermore, maintenance work orders play an important role in FM as they can be used to keep the records and history of maintenance tasks (Lavy et al., 2019). As an alternative solution used for addressing the challenges discussed, using decision-making methods can increase the consistency in FM practices and therefore is discussed in the following subsection.

4.3.2 Decision-Making Methods Used in Prioritization

Strategic decision-making requires the selection of optimal alternative from a set of options. The pairwise comparison allows individuals to decrease the complexity of decision-making by breaking down the problems into tractable ones (Dixit, 2018). Various studies used different decision-making methods for prioritizing a set of alternatives. The following four methods are provided reflecting widely applied examples in prioritization and decision-making with a systematic approach.

4.3.2.1 Analytical Hierarchy Process

Analytical Hierarchy Process (AHP) was developed by Saaty (1990) to include a combination of objective and subjective data for creating a priority hierarchy for a set of criteria and sub criteria. The method uses pairwise comparison between the criteria and subcriteria in matrices to prioritize them using a scale of 1 to 9, 9 being the most preferred. These numbers are assigned to each criterion relevant to other criteria. The same matrices are used to calculate associated weight for each criterion. The alternatives are then prioritized based on the criteria and sub-criteria considering their associated rankings (Saaty, 2008). An example of AHP implementation in industrial maintenance can be found in a study conducted by Ohta et al. (2018). They implemented AHP methodology in their study to select the proper maintenance strategy for plant maintenance based on cost, quality, safety, value added, and viability.

4.3.2.2 Analytic Network Procedure

Same as the previous method, the Analytic Network Procedure (ANP) method was developed by Saaty (2008). The difference between this method and AHP method is that ANP allows more complexity, interdependency, and relationship between the criteria (Sipahi & Timor, 2010). Chemweno et al. (2015) implemented ANP in their study for selecting the appropriate risk assessment techniques.

4.3.2.3 Priority Criterion

This method prioritizes the alternatives based on pre-assigned criteria extracted from historical data or assigned by experts based on their judgements. In other words, the responsible individuals prioritize alternatives based on a set of defined criteria (Dekker & Scarf, 1998). An example of this approach is implemented by Yusof et al. (2012). Their study requests residential building tenants to prioritize maintenance tasks based on their preferences. In addition, Dekker and Scarf (1998) prioritized aircraft maintenance needs using a set of priority criteria that the engineers selected.

4.3.2.4 Technique for Order of Preference by Similarity to Ideal Solution

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method that was developed by Hwang and Yoon (1981). In this method, the alternatives are ranked based on the "shortest Euclidean distance from the ideal solution and the farthest Euclidean distance from the negative ideal solution" (Tzeng & Huang, 2011, p.69). The ranking is performed using a set of alternatives, criteria, performance ratings, and weights. The main difference between this method and AHP is that AHP has a pairwise comparison while in TOPSIS, all alternatives are compared together at once. Shyjith et al. (2008) and Ding et al. (2014) implemented TOPSIS in their study for selecting the optimal maintenance policy.

In addition to these methods, the Failure Mode and Effect Analysis (FMEA) method was used in prioritizing the failure modes based on risk management considering failures and their effect on the assets. It uses Risk Priority Number (RPN) to rank the failure causes based on occurrence probability, the severity of effect, and detectability. The RPN represents the risk priority of the issues while the criticality of failure mode is based on occurrence probability and severity (Tay & Lim, 2006). Layzell and Ledbetter (1998) used the FMEA methodology to reduce the risk of failures in automotive cladding. They determined the RPN based on the probability of occurrence, severity of effect, and probability of non-detection. Yang et al. (2018) used the FMEA method for HVAC in order to prepare a guide for data collection and data-driven model development.

The methods mentioned above are also used in combination to address the ranking of a set of alternatives. Özcan et al. (2017) used the combination of AHP and TOPSIS methodologies to select the optimal maintenance strategy for plant maintenance. Selim et al. (2016) used a combination of TOPSIS and FMEA together to address the cost of maintenance in an international food company.

In order to study the benefits of implementing data-driven decision-making methods for processing maintenance work orders, data collection from wide range of facilities and individuals are needed. Therefore, a survey questionnaire was conducted to collect information about criteria selection and ranking for prioritizing work orders as well as data collected following the maintenance tasks among different facility types and sizes. The following sections describe the process taken for conducting the survey questionnaire as well as the results of the questionnaires.

4.4 Methodology

Based on literature review and interviews conducted in chapter 3 in which existing practices for work order processing were explored in different facilities, this research focuses on collecting data from a wider range of facilities and individuals in order to include wider range of perspectives and practices and perform a more comprehensive analysis. The following steps were taken to conduct this study.

Step 1: Based on the prior interviews conducted by the authors (chapter 3), a survey questionnaire was prepared and conducted to collect information about industry practices in terms of work order processing.

Step 2: After determining the participants' demographic information, two types of analysis was conducted. First, a descriptive analysis was conducted to present the results of criteria selection and ranking and compare the results among different facility types, facility sizes, and years of experience. The descriptive analysis also determined the common data used in different stages of work order processing. Second, an inferential statistical analysis was conducted to investigate the possible relations between facility types, facility sizes, and years of experience with criteria selection and ranking.

Step 3: The results of the survey were used to test the implementation of a decision-making method in order to address some of the existing gaps and determine the challenges associated with decision-making methods.

In addition to the question structure, visual layout, format, and flow, reliability and validity are critical in the survey design for accuracy and consistency. Reliability is defined as "The extent to which results are consistent over time and an accurate representation of the total population under study is referred to as reliability and if the results of a study can be reproduced under a similar methodology, then the research instrument is considered to be reliable" (Golafshani, 2003, p.598). To address the reliability of the data collected from survey, facility information such as type and size of the facility as well as background information of the survey participants such as years of experience and level of involvement in processing work orders were requested. With this information, the consistency of results from different individuals and facilities can be explored to show the representation of the sample group in the entire population. Furthermore, such approach allows the categorization of survey results into groups to explore the patterns and relationships between different factors including the years of experience, and type of facility with their impact on selecting and ranking of the criteria.

Validity is “how well the collected data covers the actual area of investigation” (Taherdoost, 2016, p.28). Literature review and a pilot study was conducted to address the validity of the survey. In the pilot survey process, the survey was sent to two facility management experts involved in processing work orders with more than 20 years of experience in different facility types to confirm the clarity of survey language and the development of questions that address the intended aspects. Based on the feedbacks received, the survey questionnaire was adjusted as follows: Firstly, the order of the questions was modified where the questions requiring the years of experience, facility type, facility size, and selection and ranking of criteria were marked as required. A question was also added at the beginning of the survey to eliminate responses from participants that have not been involved (directly or indirectly) in processing maintenance work orders.

4.4.1 Survey Questionnaires (Step 1)

A quantitative and descriptive study was designed. The data were collected through a survey questionnaire and descriptive and inferential statistical analysis were conducted to draw insights from the data collected.

Based on the interviews conducted in previous chapter (chapter 2), a survey questionnaire was prepared (Appendix A) to collect information about the criteria and their associated rankings used by individuals in different types of facilities for prioritizing work orders. The questionnaire also collected information about data requirements for processing work orders. Using survey questionnaire allows collecting information from a wider range of individuals and facilities reflecting and representing a more realistic and robust results.

To conduct the survey questionnaire, an application was submitted to the institutional review board (IRB) at Virginia Tech under the protocol number IRB- 20-879. According to the study objectives, IRB determined that the proposed activity is exempted for further review.

In order to recruit participants involved in processing work orders, the survey was posted online on the Qualtrics website with the account provided by Virginia Tech. In the first phase, individuals from the International Facility Management Association (IFMA) were contacted through professional connections. In addition, they were recommended by the personal network of researchers, and they were contacted by emails to participate in the survey. The survey was posted on an online platform (LinkedIn), in the second phase.

A total of 95 responses were collected between August to November 2021, from which 18 responses were excluded as the responders were not directly nor indirectly involved in processing work orders. Additionally, six responses were excluded since they did not complete the survey. Subsequently, 71 responses were analyzed for this study. Even though the nationwide population of facility managers was reported around 100,000 by U.S. Bureau of Labor Statistics in 2021), the number of FM professionals directly involved in work order processing in each facility is very limited. Acknowledging the fact that the authors are not making inferences about the entire FM population based on the sample size, the results of this study reflect the valuable feedback of participants with their experience in FM profession.

4.4.2 Analysis (Step 2)

First, the survey was analyzed to determine participants' demographic information. In the next step, a descriptive analysis was conducted to present the overall results of criteria selection and ranking. The results when then categorized by facility type, facility size, and years of experience. Also, an inferential statistical analysis was conducted to investigate the relation between years of experience, facility type, and size with criteria selection and ranking. The survey structure allowed the participants to select different numbers of criteria to better understand their practices, therefore, the rankings were normalized by converting the rankings to scores and using the average and standard deviation of each response for normalization of the scores. Multiple linear regression is used for studying the strength of relationships between two or multiple variables and therefore, was used to investigate the relations between years of experience, facility type, facility size with criteria ranking. Finally, the data was analyzed to determine the common data between information used for processing work orders and information collected following the completion of the maintenance tasks. Therefore, average and distribution (frequency) of the criteria selected were determined. Determining the common data allows investigating similarities in different phases of addressing maintenance work orders for developing comprehensive framework and data requirements.

4.4.3 AHP Approach (Step 3)

The criteria and ranking collected from the survey for educational institutions were used to test and investigate the implementation of decision-making methods, in this case AHP. The AHP method was selected over the other methods due to the following reasons. First, AHP is a flexible and robust multiple criteria decision-making method. Second, nine criteria were selected for the implementation as the average number of criteria selected by the participants were 9. The goal of this implementation was to address some of the gaps discussed and determine the challenges with implementing such methods. Additionally, the implementation can help FM professionals to understand how to use the decision-making methods and criteria identified in this study and implement their ranking to provide guidance and support for their decision-making.

4.5 Results

This section first provides the results of the survey analysis determining participants' demographic information. In the next step, the overall criteria selection and ranking is presented. The result of the analysis also shows the comparison of criteria selection and ranking based on facility type, size, and years of experience. The top nine criteria were selected since the average number of criteria selected by the participants was nine. Using an inferential statistical analysis, the possible relation between years of experience, facility type, and size with criteria selection and ranking are presented. The last section of survey analysis presents the common data between processing work orders and data collected following the completion of maintenance tasks. The section concludes by providing an example of AHP implementation for prioritizing a set of work orders.

4.5.1 Participants' Demographic Information

Based on survey results, the following sections provide descriptive information about participants' level of involvement, years of experience, facility type, facility size, and facility location.

Figure 4.1 presents how many participants have been directly involved in processing work orders and how many have been indirectly involved in the process. Based on the results, more than half of the respondents have been directly involved in processing work orders.

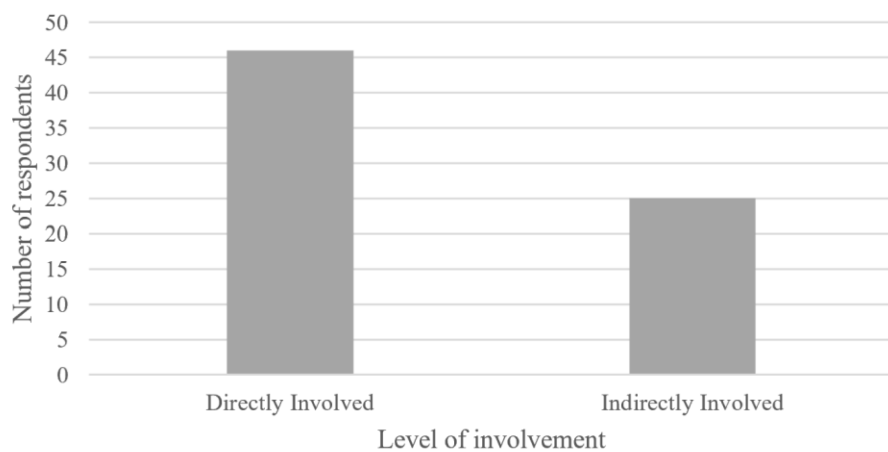

Figure 4.1. Percentage of participants in each level of involvement in processing work orders

As a result of the literature review as well as interviews conducted (chapter 3), it is revealed that years of experience helps with better knowledge of the facility hence positively impacting the work order processing. Participants were asked to indicate their years of experience in facility management to identify its impact on the selected criteria and their rankings. As Figure 4.2 presents, 32.4% of participants had 10 to 20 years of experience while only 2.8% of participants had less than one years of experience.

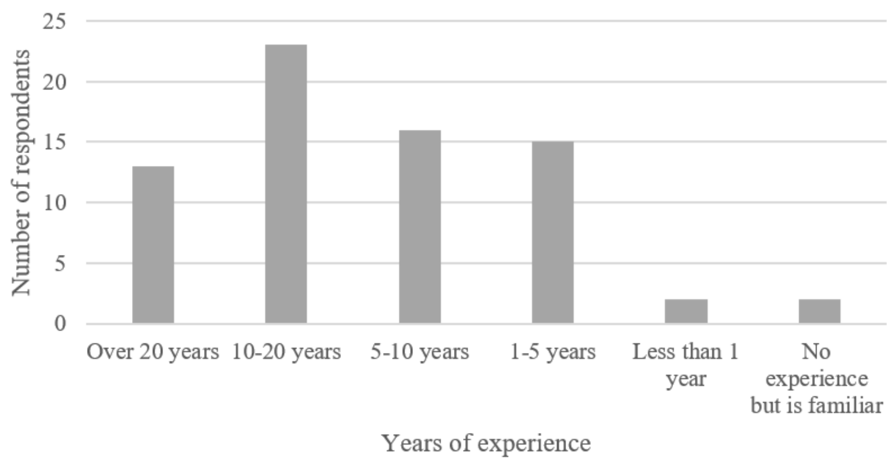

Figure 4.2. Years of experience of respondents

Furthermore, the participants were asked to provide information about their facility type to determine the impact of facility type on the criteria selection as well as their assigned ranking. The majority of respondents worked in commercial facilities as well as educational institutions covering 60% of the total responses presented in Figure 4.3. The lowest response rates were from healthcare and industrial facilities each having only one participant. Therefore, the detailed comparison between facilities did not include facility types with small representation.

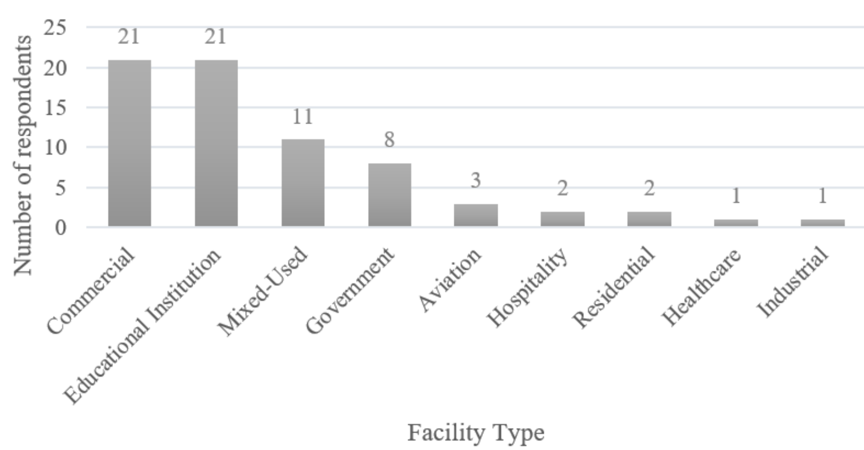

Figure 4.3. Number of responses by facility type

The range of facility size and the number of buildings in the participants' portfolio were also requested to determine the impact of the facility size on criteria selection and ranking. Out of the 71 responses, 30 facilities (42.25%) were reported providing services to more than 50 buildings (as presented in Figure 4.4). Additionally, 40 participants (56.33%) indicated that they manage all the buildings within their facilities while 31 (43.66%) indicated managing a range of 6 to 30 buildings in their facilities.

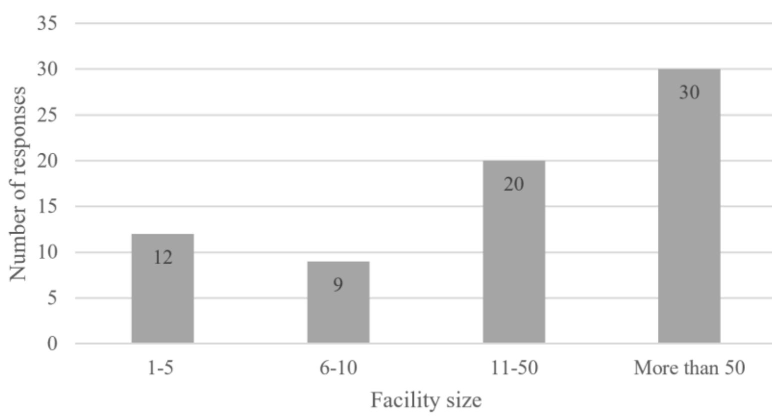

Figure 4.4. Number of responses based on facility size (number of buildings)

Although the majority of responses (71.8%) were received from individuals within the U.S., there were few responses from other countries including Canada, Australia, Brazil, Iran, and Egypt.

4.5.2 Criteria Selection

Figure 4.5 presents the frequency of each criterion based on the responses. The results indicate that the frequently selected criteria were “level of severity (hazard)”, “availability of staff”, “severity of failure”, “occupants’ preference/satisfaction”, and “availability of resources” respectively. The five least selected criteria were “building age”, “end date (completion date)”, “remaining lifecycle”, “energy usage”, and “distance from the facility”. On average, nine criteria were selected for processing work orders while the highest number of criteria selected was 23 and the lowest number selected was three.

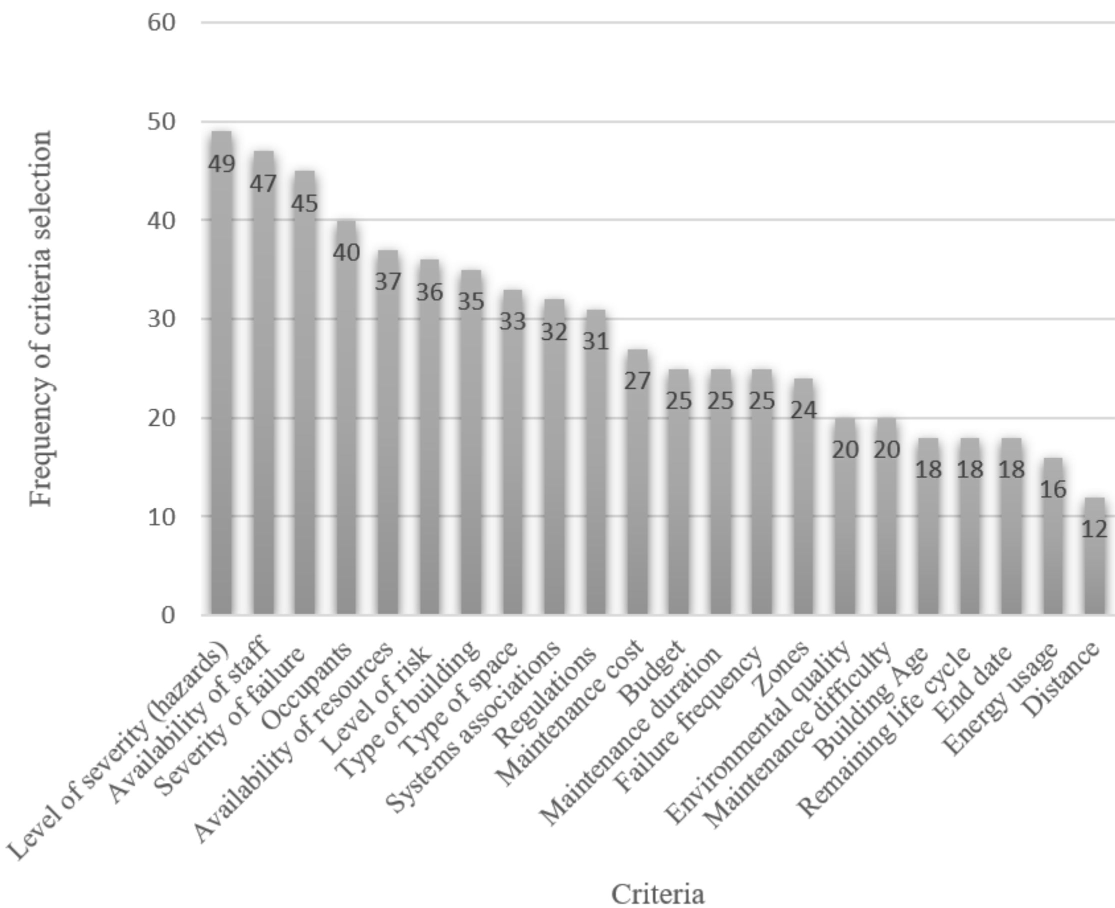

Figure 4.5. Frequency of a criterion selection by the respondents

The additional criteria considered by facilities included: “type of work order”, “impact of failure on business operations and facility function”, “impact on occupant's mission”, “potential for immediate or long-term damage to facility if not prioritized”, “business impact”, “corporate policy in terms of preventative maintenance schedules”, “importance of the requester’s role (e.g., vice president)”, and “importance of requester’s location (e.g., issue in the president's house)”.

To investigate the differences of number of criteria selected among individuals with various years of experience, the average number of selected criteria by individuals in each category of experience were compared in Figure 4.6. The individuals with zero or less than one year of experience were disregarded due to the small sample size and it was observed that the average number of criteria selected by participants increased with their level of experience.

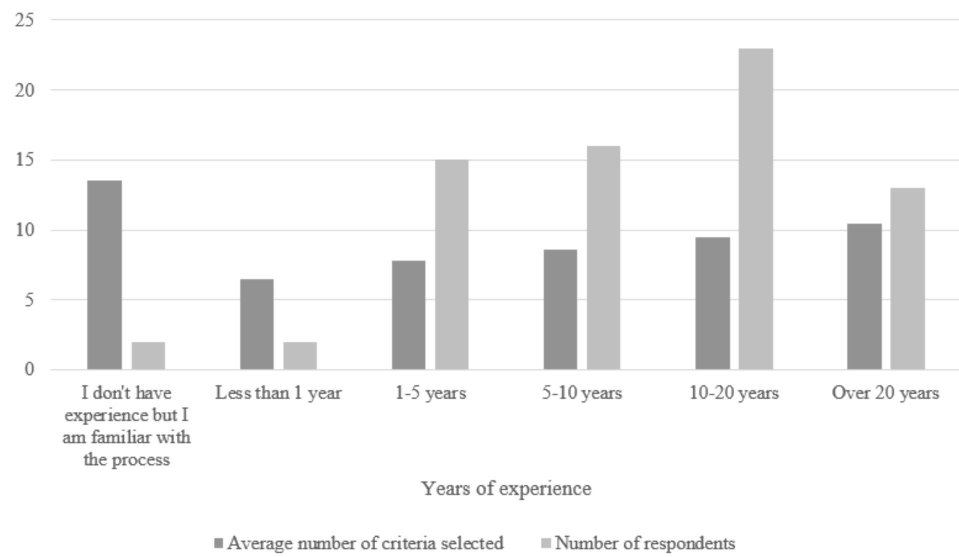

Figure 4.6. Average number of criteria selected by individuals based on years of experience

In addition, considering the validity of the analysis, with the small sample size of healthcare, industrial, residential, hospitality, and aviation facilities (Figure 4.3) the average number of criteria selected based on facility types were only compared for commercial, educational institutions, mixed-used, and government facilities. Figure 4.7 presents the average number of criteria selected among different type of facilities.

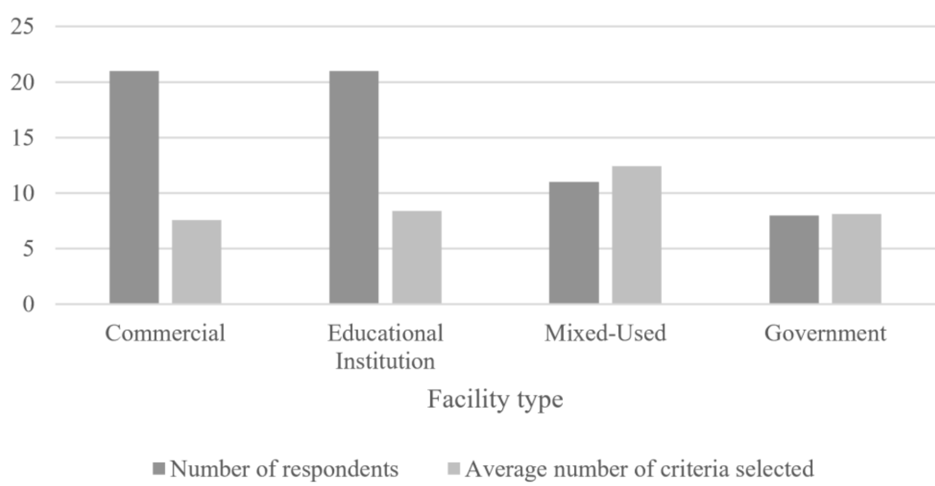

Figure 4.7. Average number of criteria selected by individuals based on facility type

To further study the impact of facility type, the distribution of criteria selection was compared for two facility types. Educational institutions and commercial facilities had the highest representation in the survey results with the same number of participants. Hence, the distribution of criteria selection in the survey was presented only for these two facility types. Additionally, to better understand the differences, the selection percentage in general was also determined. As Figure 4.8 presents, the frequency of the selected criterion differed for some of the criteria including availability of staff, level of risk, occupants' satisfaction, and codes and regulation between the two facility types.

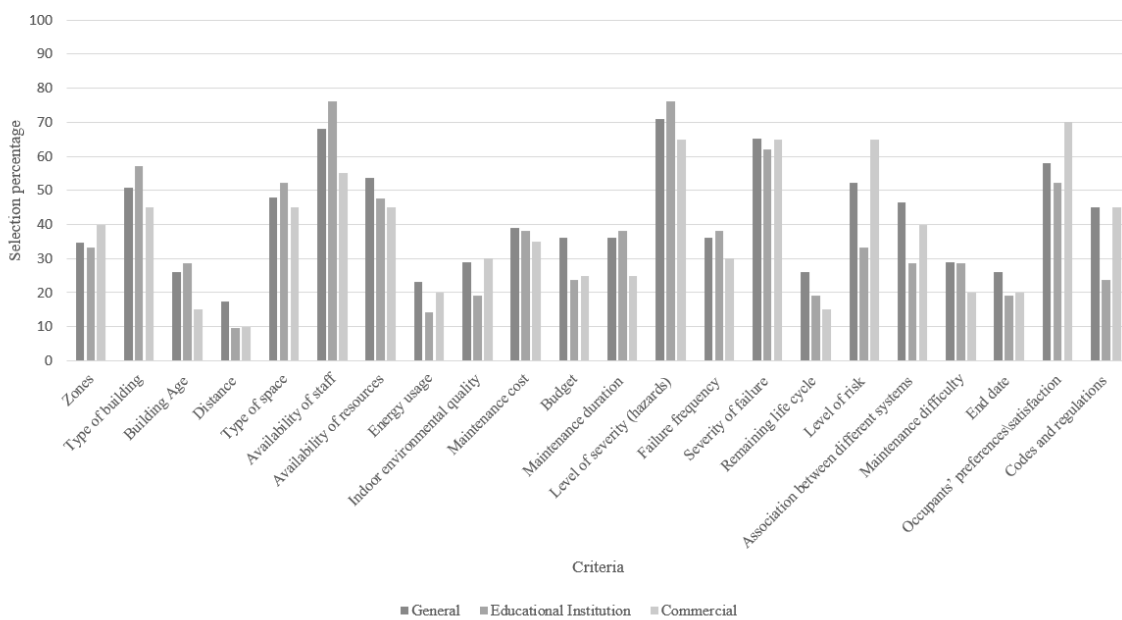

Figure 4.8. Selection percentage for each criterion based on facility type (Educational Institutions and Commercial facilities)

The average number of criteria selected among facilities with different sizes did not vary as presented in Figure 4.9. Considering the finding, it can be assumed that when the number of building increases, not all buildings are managed by the same person/team, which requires further investigation.

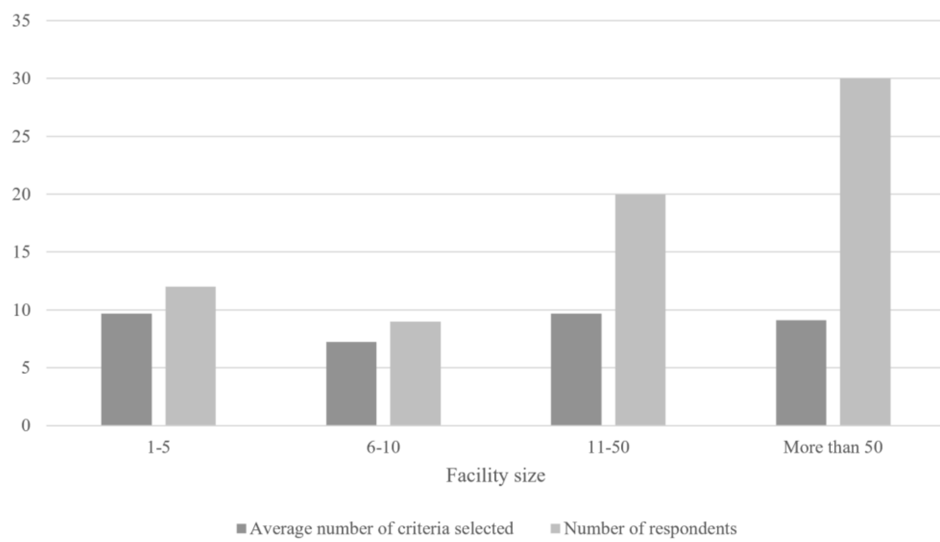

Figure 4.9. Average number of criteria selected by individuals based on facility size

4.5.3 Criteria Ranking

As discussed in the methodology, an inferrential statistical analysis was conducted to compare the ranking among different participants, and to do so, the rankings were converted to scores and were normalized. Considering the top nine (average number of criteria selected) criteria ranking, level of severity was selected by the majority of participants with the highest ranking in terms of significance when processing work orders. However, categorizing the responses by years of experience (the low level of experience as opposed to high level) shows that there are differences between the criteria selection and ranking among participants with different years of experience (Table 4.2). For instance, with increased years of experience, the criteria selected, and their rankings were in similar levels among the participants, and they differed from the selection and ranking of other participants with less experience. For instance, the responses received from participants with over 20 years of experience were more similar as opposed to the responses of participants with less than 5 years of experience highlighting higher level of differences and variability among participants with less years of experience. The differences existed when categorizing the responses by facility type (Table 4.3) and facility size (Table 4.4) as well.

Table 4.2. Top ranked criteria based on years of experience

Criteria	Overall Ranking	1-5 Years	Over 20 Years
Type of building	6	7	7
Type of space	9	9	-
Availability of maintenance staff	3	4	4
Budget	-	-	8
Level of severity (hazards)	1	1	1
Severity of failure	2	3	2
Level of risk	5	5	5
Availability of resources	7	6	-
Indoor environmental quality	-	-	9
Association between different equipment/system	8	8	-
Occupants' preferences\satisfaction	4	2	3
Codes and regulations	-	-	6

Table 4.3. Top ranked criteria in different types of facilities

Criteria	Overall Ranking	Educational Institution	Commercial
Type of building	6	4	6
Type of space	9	5	
Availability of maintenance staff	3	2	5
Level of severity (hazards)	1	1	1
Failure frequency	-	9	-
Severity of failure	2	3	4
Level of risk	5	8	3
Availability of resources	7	7	7
Association between different equipment/system	8	-	9
Occupants' preferences\satisfaction	4	6	2
Codes and regulations	-	-	8

Table 4.4. Top ranked criteria based on facility sizes

Criteria	Overall Ranking	1-5 Buildings	11-50 Buildings
Type of building	6	7	6
Type of space	9	-	

Availability of maintenance staff	3	8	7
Maintenance cost	-	-	9
Level of severity (hazards)	1	6	1
Severity of failure	2	2	2
Level of risk	5	4	3
Availability of resources	7	3	8
Indoor environmental quality	-	9	-
Association between different equipment/system	8	-	5
Occupants' preferences\satisfaction	4	1	4
Codes and regulations	-	5	-

Considering the differences between the sample sizes and their limitation in this study, the authors implemented multiple linear regression, to study the possibility of significant correlation between the three factors: years of experience, facility size, and facility type with criteria ranking. Based on the analysis, facility type had significant impact on ranking of some of the criteria including maintenance duration (Prob>F: 0.0375) and budget (Prob>F:0.0276). Years of experience also had impact on criteria ranking including end date (Prob>F:0.0001), maintenance duration (Prob>|t|: 0.0452 for 1-5 years of experience), failure frequency (Prob>|t|: 0.0122 for 10-20 years of experience), and severity of failure (Prob>|t|: 0.0438 for 0 years of experience but familiar). However, the facility size did not greatly impact the ranking of criteria having significant impact only on availability of maintenance staff.

4.5.4 Data Collected After Performing the Maintenance Tasks

According to interviews conducted in previous studies by the authors (Ensafi & Thabet, 2021, chapter 3), most facilities collect information after the maintenance tasks are completed, however, not all facilities benefit from the data collected for future work order processing. Additionally, due to lack of information requirements, facility management departments are not necessarily collecting information that can be useful for processing work orders. Therefore, an analysis was conducted to determine what information are collected after the maintenance tasks are completed and if there is any overlap between the information collected and information used for processing work orders.

Among the 71 responses, two respondents marked that they do not collect information after the maintenance tasks are completed. On average, five criteria were frequently selected by respondents as information collected following the maintenance task completion (Figure 4.10). Among the criteria provided, total hours spent on the tasks and issue description were the most selected (58 and 55 respectively) while percentage completion of the tasks in each visit and difficulty with repair were the least selected (14 and 9 respectively).

Figure 4.10. Data collected following the maintenance tasks

Other criteria indicated by the respondents include asset information, contracts and issue resolution information, safety and security information and experience, complaints from maintenance personnel, obstacles encountered, probability of repeated incidents, deficiencies noted as well as recommendations and opportunities for improvements, quality control and quality assurance notes, who performed the work, what was done to complete the work, who closed the work order out, whether the work was completed on time or whether work order was overdue, photos, and final completion survey sent to originator of work order to ensure work is completed to client/occupants' satisfaction level.

4.5.5 Common Data Between Work Order Processing and Information Collected Following the Maintenance Tasks

Figure 4.11 presents the criteria selected by participants for processing work orders versus the information collected following the maintenance tasks performed. Understanding and identifying information requirements for processing work orders can help with developing data requirements to consistently and continuously collect useful data after the maintenance tasks are completed. For example, while 20 participants highlighted the importance of maintenance difficulty for processing maintenance work orders, only nine participants selected the difficulty of repair as information collected following the maintenance tasks.

Determining common data among different stages of work order processing allows avoiding the collection of data that is not important as well as considering important information that can be used to enhance work order processing. For example, maintenance cost was considered by 27 participants for processing work orders while the cost of material and resources was captured by 53 of the participated in the study.

Also, further data analysis can be conducted to identify possible influential factors. For instance, if the duration of maintenance task is captured as well as the name of the person who performed the tasks, the data collected can be used to understand the performance of facility staff.

Selection Frequency	Criteria for processing work orders	Information collected following maintenance task	Selection Frequency
47	Availability maintenance staff	Number of crew members	46
37	Availability of resources	Quantity of spare parts required	29
		Material used	1
20	Indoor environmental quality	Safety and security information	1
49	Level of Severity (hazard)	Issue description	55
27	Maintenance cost	Material/resources cost	53
25	Maintenance Duration	Duration of task (start and end date)	53
		Total hours spent on the task	58
		Number of visits to complete the task	20
		Percentage completion in each visit	14
25	Failure Frequency	Likelihood of repeat incidents	1
20	Maintenance Difficulty	Difficulty with repair	9
		Obstacles encountered	1
		Complaints from maintenance personnel	1
18	End Date	Whether the work was completed on time or was overdue	1
40	Occupants' Satisfaction/Preference	Client/occupants' satisfaction	4
31	Codes and Regulation	Contracts and issue resolution	3
32	Systems Association	Any tracked assets the work was associated with	1
25	Maintenance type, type of work	What was done to complete (work description)	2
28	Details of problem, Exact location of issue or asset	Issue description	55

Figure 4.11. Data overlap between data used for processing work orders and data collected following the maintenance tasks

While the numbers in Figure 4.11 are good indicators of conceptual similarities between information used for processing work orders and information collected following the maintenance tasks, further analysis was performed. For instance, based on Figure 4.11, the selection of “Availability of maintenance staff” criterion is almost equal to collection of “Number of Crew” information following the maintenance tasks. However, out of 47 participants who selected “Availability of maintenance staff” criterion, 16 of them did not select “Number of Crew” information collection following the maintenance tasks. Additionally, 15 of the participants who indicated collecting “Number of Crew” information, did not select “Availability of maintenance staff” criterion for their work order processing. Differences among criteria selection and data collected following the maintenance tasks were identified for other information included in Figure 4.11. Such differences highlight the importance of identifying information requirements to collect data that is needed while also using the beneficial data that is already being collected.

4.5.6 Implementation of Decision-Making Methods in Prioritization

Generally, studies conducted on prioritization have used methods such as AHP to assign weights to criteria for prioritizing a set of alternatives. The weights assigned to the criteria are subjective numbers. To better explain the process, the next section describes the steps taken in the AHP method as an example of decision-making methods using the rankings and prioritization of the top nine criteria from the survey.

The survey results indicated that the following criteria were selected as the top nine for educational institution facilities: level of severity, availability of maintenance staff, severity of failure, type of building, type of space, occupants’ preferences/satisfaction, availability of resources, level of risk, and failure frequency. Using the ranking from the surveys (Table 4.5, 9 being the most important and 1 the least), each two criteria were compared (Table 4.6) and the value indicating their importance in relative to each other were estimated. The values were then normalized (using geometric mean $(\prod_{i=1}^{n} x_i)^{\frac{1}{n}} = \sqrt[n]{x_1\, x_2\, \ldots\, x_n}$) and the weight (dividing the geometric mean for each criterion by sum of all the means) for each criterion was estimated (Table 4.7).

Table 4.5. Top nine criteria

	Criteria	Score
A	Level of severity (hazards)	9
B	Availability of maintenance staff	8
C	Severity of failure	7
D	Type of building	6
E	Type of space	5
F	Occupants' preferences\satisfaction	4
G	Availability of resources	3
H	Level of risk	2
I	Failure frequency	1

Table 4.6. Pairwise comparisons of the nine criteria

Criterion	A	B	C	D	E	F	G	H	I
A	1.000	0.889	0.778	0.667	0.556	0.444	0.333	0.222	0.111
B	1.125	1.000	0.875	0.750	0.625	0.500	0.375	0.250	0.125
C	1.286	1.143	1.000	0.857	0.714	0.571	0.429	0.286	0.143
D	1.500	1.333	1.167	1.000	0.833	0.667	0.500	0.333	0.167
E	1.800	1.600	1.400	1.200	1.000	0.800	0.600	0.400	0.200
F	2.250	2.000	1.750	1.500	1.250	1.000	0.750	0.500	0.250
G	3.000	2.667	2.333	2.000	1.667	1.333	1.000	0.667	0.333
H	4.500	4.000	3.500	3.000	2.500	2.000	1.500	1.000	0.500
I	9.000	8.000	7.000	6.000	5.000	4.000	3.000	2.000	1.000

Table 4.7. Weight of each criterion

	Criteria	Product	Geometric Mean	Weight
A	Level of severity (hazards)	0.000936657	0.46080	0.3535
B	Availability of maintenance staff	0.002703667	0.51840	0.1767
C	Severity of failure	0.008992505	0.59245	0.1178
D	Type of building	0.03600823	0.69119	0.0884
E	Type of space	0.18579456	0.82943	0.0707
F	Occupants' preferences\satisfaction	1.384277344	1.03679	0.0589
G	Availability of resources	18.43621399	1.38239	0.0505
H	Level of risk	708.75	2.07358	0.0442
I	Failure frequency	362880	4.14717	0.0392

Using the value for each criterion for each work order and the weights estimated in the previous step, the final weight for each work order was estimated and the work orders were ranked and prioritized based on the estimated weights (Table 4.8).

Table 4.8. Work order ranking and prioritization

A	B	C	D	E	F	G	H	I	Final Weight	Rank
0.353	0.176	0.117	0.088	0.070	0.058	0.050	0.044	0.039		
1	1	2	1	1	3	2	1	1	1.2782	8
4	2	3	4	4	4	2	4	3	3.3726	3
5	2	5	5	5	5	2	5	3	4.2196	1
4	2	4	5	4	5	2	5	1	3.6012	2
1	2	1	3	3	1	2	3	1	1.6252	6
1	1	1	5	2	1	1	1	1	1.4172	7
4	2	4	3	3	5	2	4	2	3.3504	4
2	2	2	1	2	3	2	1	1	1.8772	5

	Weight	Semi-annual service of exhaust fan in Building H	Fan coil unit burned out on the 3rd floor of library	Elevator in building A not working	Building A, room 210, water leaking into the clean room	Monthly inspection of fire extinguisher in mechanical room, Building B	Building A, Men's restroom on 2nd floor, old soap dispenser should be removed	Building B, leak in room 133 coming from hot water booster	Building H, Room 159, lights out

4.6 Discussion

While previous studies have explored the use of selected criteria for processing and prioritizing work orders, this chapter investigated the full list of criteria used by various facilities for processing their work orders. Based on the results of the survey questionnaires, the number of criteria selected varied among the participants ranging from 3 to 23. Considering the range of number of criteria selected and based on studies conducted on human cognitive limitations (Hollnagel & Woods, 2005), a hypothesis can arise that due to cognitive workload and human limited cognitive capacity, it would be complicated to consider more criteria at once.

This chapter also investigated the impact of external factors such as facility type and size and internal factor such as years of experience on criteria selection and their rankings. The average number of criteria selected among FM professionals varied based on years of experience and facility type. The results presented the selection of additional criteria by individuals with more experience which can be a good indicator of importance of individuals experiences to perform work order processing. While increasing the number of criteria used for processing work orders can imply that more aspects are considered for prioritizing alternatives by individuals with high level of experiences, the results need to be validated by considering the impact of other factors such as organizational goals. The variety in number of criteria selected across individuals highlights the need for identifying the optimum number of criteria to collect comprehensive information while avoiding collecting excessive information. Furthermore, there should be a balance between the processing time and the quality of results. For instance, it’s important to study if using more criteria will lead to longer processing time and if yes, is the time extension and the cost associated with it worth better results. Determining the optimum number of criteria will help facilities to collect comprehensive information while avoiding collecting excessive information.

Considering the overall criteria ranking, level of severity, severity of failure, and availability of maintenance staff respectively were ranked as the top three criteria selected by the participants. The rankings were compared among different facility types, sizes, and years of experience and the results presented differences between the categories. Such differences could be an indication of differences in organizational values among different facility types leading to different criteria selection and ranking and require further investigation. It is important to determine such factors as a single list of criteria and ranking is not practical solution for all facilities. The developed frameworks should not be generalized to all facilities and should have flexibility to be applicable to various facilities considering their differences and the implementation of their goals.

The survey structure let the participants to select and rank their preferred number of criteria, in other words, participants did not have to select and rank all criteria provided in the survey. Such option impacted the statistical analysis. While the results of the regression analysis marked the possible correlation between external factors and criteria selection and ranking, these results were impacted by the sample sizes in each category. Therefore, the authors have focused on presenting the results with descriptive techniques. In order to further study the impact of each factor and validate the results of this research, bigger sample sizes are required. Additionally, larger sample sizes will allow investigating the impact of multiple factors (e.g., facility type and size) simultaneously.

Most of the previous studies are focused on the processing and prioritization stage while this chapter explored the data collected following the completion of the maintenance tasks in existing practices and the benefits it can provide for processing future work orders. Additionally, previous studies have focused on one specific stage of work order processing while this chapter investigated the common data between different stages of work order processing considering the connection between different stages for enhanced FM. Although most facilities collect information after the maintenance tasks were completed, not all of them benefited from the data collected for future work order processing. In other words, while participants highlighted the importance of some of the criteria for processing work orders, they did not collect that information following the maintenance tasks completion. On the other hand, the data they collected following the maintenance tasks were not necessarily beneficial or used for processing maintenance work orders. Understanding common information between different stages of processing work orders can help with developing comprehensive data requirements to address the existing challenges with strategic decision-making and can enforce what data should be collected and in what format. FM professionals should consider the big picture and the connection between different stages of work order processing. Such approach helps with collecting sufficient information and eliminates data duplication to save time, enhance the quality of services, and support the future decision-making processes. Insufficient information can force the operator to interpret based on limited amount of information while providing excessive information may also lead to coping strategies.

Although decision-making methods can be used to enhance the consistency in prioritizing a set of alternatives, there are some challenges and gaps in their application. First, the alternatives usually have multiple attributes, consequently, considering one attribute for each alternative is not realistic. On the other hand, due to limited human cognition capacity and as the result of information overload, humans cannot reliably compare multiple pairwise alternatives with different attributes at the same time. Therefore, their decision-making is negatively impacted requiring systematic decision-making for complex decisions with conflicting criteria (Dixit, 2018; Hollnagel & Woods, 2005). Therefore using 5-9 criteria have been suggested for implementing AHP considering human working memory capacity as an example. Second, the comparison of alternatives is different and more realistic when it is performed during the actual maintenance work order prioritization compared to when it is performed outside of maintenance context (chapter 3). For instance, distance was marked as one of the least important criteria for work order processing. While the level of importance for distance is correct, compared to other criteria such as risk level, prior chapter (chapter 3) have revealed that individuals consider distance with higher priority in some cases where it increases the convenience of the staff (e.g., assigning work orders located in a shorter distance to crews). Such results highlight the significance of determining the list of criteria and their ranking from investigation of actual work order processing performed. Third, humans do not assess the pairwise comparison matrices in a consistent manner as they use a combination of quantitative and qualitative analysis (Dixit, 2018). Fourth, possible influential factors such as years of experience should be identified and considered when prioritizing a set of alternatives to increase consistency (chapter 3) and remove the impact of judgements and possible biases. Fifth, the weights estimated for different attributes are not updated over time unless the rankings are investigated repeatedly (Ensafi & Thabet, 2021). Sixth, some staff may still rely on their knowledge and judgement instead of following the prioritization strategy. Seventh, numerical values should be assigned to categorical data such as space type in order to implement them in the final ranking. Eighth, not all work orders have value for all the criteria determined. For example, elevators do not have a designated space as they serve the entire building. The same value used for building type was therefore used for the space type, but such approach may impact the final results.

As large amount of data is generated by various assets within the facilities and are available to facility managers, the concept of big data can assist the facilities with extracting meaningful information and patterns. Such approach addresses some of the challenges with user-driven decision-making but requires development of data requirements as well as continuous and consistent data collection.

4.7 Conclusion

This chapter presented the results of a survey questionnaire conducted to investigate the overall criteria selection and ranking and to compare the results among different facility types, sizes, and years of experience. A descriptive and an inferential statistical analysis were conducted to gain insight from the data collected and investigate the possible impact of different factors on criteria selection and ranking. The chapter also discussed the use of various decision-making methods to address some of the challenges with existing practices and presented an example of implementation of AHP. The chapter concluded with discussing the challenges with implementing decision-making methods and suggestions on using data-driven methods such as machine learning.

Although the data collected from the survey questionnaire was sufficient to perform a descriptive analysis and present the differences among different categories, more responses are needed in order to have larger sample sizes (e.g., healthcare facilities) to validate the statistical analysis and the possible correlation between the factors discussed.

Due to the challenges with decision-making methods and to benefit from historical data collected, the authors are planning to implement data-driven decision-making, specifically neural network, to automate the prioritization of future work orders. Machine learning (ML) methods and algorithms have been used by different researchers in various fields including construction (Ensafi et al., 2022) and facility management (Zarindast & Wood, 2021; Canizo et al., 2017) to address the challenges with existing practices. Having access to historical maintenance data and work order history can assist facility managers with processing future work orders as well as determining correlation between different factors. The use of ML allows covering more criteria without resulting in cognitive workload and coping strategies. Using neural networks, the optimum number of criteria can be determined, and the importance of each criterion can be estimated based on previous knowledge and approaches used for processing work orders. Additionally, using methods such as ML allows automatic updates based on new inputs which leads to more practical solutions over time.

4.8 Acknowledgement

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CHAPTER 5: WORK ORDER PRIORITIZATION USING NEURAL NETWORKS TO IMPROVE BUILDING OPERATION [4]

5.1 Abstract

Current practices for prioritizing maintenance work orders are mainly user-driven and lack consistency in collecting, processing, and managing the large amount of work order data. While decision-making methods have been used to address some of the existing challenges such as inconsistency, they also have challenges including variation between comparison during the actual prioritization task as opposed to those outside of maintenance context. The data analytics and machine learning methods can help with extracting meaningful and valuable information, finding patterns, and drawing conclusions from the available data to support future decision-makings. Such methods have benefits including faster prioritization performance leading to less failure and downtimes, reduced impact of knowledge loss, decreased cognitive workload, identification of errors for adjusting the system, and determination of important factors impacting work order processing to support the development of data requirements.

This chapter summarizes the background on existing gaps in processing maintenance work orders and provides an overview of machine learning methods to support the decision-making in prioritizing work order. The chapter then discusses the work order data of an educational facility and presents information on data exploration and data cleaning approach providing insights gained from their maintenance work order data. The insights gained present challenges such as submission of multiple work orders as one, missing data for certain criteria, long durations for addressing some of the work orders, and the correlation between criteria collected by the facility and the schedule. The chapter continues by implementing artificial neural networks to benefit from work order data collected for automatically prioritizing the future work orders. This was achieved by modifying different parameters of the neural network to minimize the mean squared error.

[4] This chapter has been submitted to an academic journal.

The results present the optimum neural network structure based on mean squared error estimated and provides the best value for each parameter used for the development of the model. The accuracy and efficiency of the developed model was validated by the facility experts of the educational facility.

Keywords: Facility Management, Maintenance Work Order, Prioritization, Artificial Neural Networks

5.2 Introduction

Facilities management (FM) is "a multidisciplinary or transdisciplinary profession drawing on theories and principles of engineering, architecture, design, accounting, finance, management, and behavioral science" (Teicholz & Techolz, 2001, p.1.3). Prioritizing maintenance work orders is one of the challenges faced by facility managers as current practices lack consistency in collecting, processing, and managing the large amount of work orders and data. Based on previous extensive literature review and interviews conducted in chapter 3, current practices heavily depend on user-driven approaches and the prioritization of work orders has been done manually or partially through management systems. This common approach used by many facility managers present many challenges.

The lack of information requirements has led to inconsistency in data collection and processing (Yang & Ergan, 2017; Lavy et al., 2019). Information requirements are needed to determine what data should be collected and how the data should be processed while also considering the organizational goals and avoiding generalization to all types of facilities (Besiktepe et al., 2020). Although some facilities collect information related to processing and performing maintenance tasks, not all of them benefit from the data collected. On the other hand, the information collected is not necessarily useful for future work order processing. The discontinuous data collection in different stages of work order processing hinders the opportunity to benefit from the collected data. Facilities need to understand the data overlap between different stages of work order processing to develop practical data requirements as described in chapter 3.

The traditional process of work order processing is impacted by individuals' knowledge, experience, workload, and some biases. There are variabilities across individuals' criteria selection and decision-making approaches leading to uncertainty, inconsistency within the input data, and poor performance as described in chapter 3. The extent of knowledge and experience of the staff who analyze the service requests can influence the work order processing (Cao et al., 2015; Tam et al., 2017). The lack of knowledge about asset performance will lead to errors and asset failure impacting the cost of O&M (Bayasteh et al., 2019; Salem & Elwakil, 2018) and occupants' safety and satisfaction (Cao et al., 2015). On the other hand, analyzing such large amount of information can lead to cognitive workload leading to different coping strategies including trading precision for speed and time, neglecting to process certain categories, stretching existing evidence to fit a new situation (Hollnagel & Woods, 2005). Furthermore, humans may be impacted by various cognitive biases such as focusing on limited objectives due to ambiguous nature of strategic decision making (Schwenk, 1985).

The existing processes require adequate staffing to fill the shifts for receiving work orders and there are mostly more work order requests than available staff for addressing them (Beauregard & Ayer, 2019). Making decisions and responding to many requests demand intensive labor hours (Chong et al., 2019). However, experienced individuals who have good knowledge of the facility are currently selected for processing work orders. At the same time, if the selected individuals leave the facility or retire, their expertise and knowledge will leave with them and may not be transferred to new individuals responsible for processing work orders.

While decision-making methods such as Analytical Hierarchy Process (AHP) (Saaty, 2008) as discussed in chapter 4 have been used to improve the consistency of prioritization, they also represent challenges and gaps in their application. First, because of information overload resulting from processing multiple attributes for each alternative and because of limited human cognition capacity, humans are not able to compare multiple pairwise alternatives with different attributes at the same time. Such difficulty negatively impacts the decision-making process (Dixit, 2018; Hollnagel & Woods, 2005). Based on the results of studies in chapter 3, the alternative comparison varies and is more realistic when performed during the actual work order prioritization task as opposed to outside of maintenance context. Third, pairwise comparison matrices are not assessed in a consistent manner by humans since they cover a combination of quantitative and qualitative analysis (Dixit, 2018). Lastly, the process and weights estimated are not evaluated, adjusted, and updated over time (Ensafi & Thabet, 2021).

The data analytics and machine learning methods can help with extracting meaningful and valuable information, finding patterns, and draw conclusions from the available data to support future decision-makings (Assaf et al., 2020; Jiang et al., 2020; Yang & Bayapu, 2019). Such methods allow faster prioritization performance leading to less failure and downtimes. They can capture the user knowledge removing the negative impact of staff leaving the facility while reducing the impact of lower level of experience and background knowledge on processing future work orders. Additionally, automating the work order processing can reduce the cognitive workload on facility staff allowing them to focus on critical thinking and emergency situations rather than routine tasks. Implementing machine learning will allow processing based on multiple inputs possibly reducing the impact of biases. Data analytics allows identifying important criteria by determining the relationship between different factors used for processing. This will also support the development of practical data requirements. Finally, an automated approach enabled by neural networks allows the automatic adjustment and update of the system based on new data and input providing a more practical solution over time. Neural networks are selected over other Machine Learning (ML) methods as they learn themselves and determine what is important without requiring a defined set of rules. Additionally, Artificial Neural Networks (ANNs) allow to consider more criteria (features) providing a more comprehensive solution as opposed to a human operator, and at the same time, it can determine the optimum number of criteria eliminating the collection of unbeneficial criteria.

The goal of this chapter was to implement ANNs into work order data received from an academic facility in order to automatically prioritize their future work orders based on their historical work orders. This chapter aims to address the following research questions: 1) Can neural network prioritize work orders based on previous schedules created to support accuracy, efficiency, and consistency (in terms of criteria used)?; 2) What is the most efficient neural network structure for prioritizing maintenance work orders?

This chapter provides an overview of machine learning methods and especially neural networks for addressing some of the challenges with exiting practices for processing maintenance work orders. In order to conduct this research, the work order data of an educational facility was used. The received work order data was analyzed and preprocessed to automated the work order prioritization using neural network. The results present the optimum model configuration as well as optimum values for different hyperparameters for implementing neural networks to automatically process and prioritize future work orders.

5.3 Literature Review

Due to the rapid improvement of technologies used for facility management, more complicated and larger amount of data are created and are available to facility managers (Cao et al., 2015). Facility managers can use different tools and platforms to capture information, perform analysis, and draw conclusion on past performance while also anticipating future trends using Artificial Intelligence (AI) and Machine Learning (ML) (IFMA, 2021). Machine learning is “the process of training a computer model on a training dataset to perform a certain task so that it will be able to perform that exact task when given new data it had not encountered before” (Assaf et al., 2020, p.173).

Recently, an increasing number of studies are adopting AI techniques and ML algorithms to address design (Feng et al., 2019), construction (Ensafi et al., 2022), and facility management challenges (Zarindast & Wood, 2021; Awada et al., 2020; Feng et al., 2017; Tabrizi et al., 2012). Researchers have implemented AI and ML to address different aspects of building operation phase including air quality (Xie et al., 2020), energy consumption (Hajj-Hassan et al., 2020; Lu & Feng, 2020; Murrieum et al., 2020; Wang & El-Gohary, 2020; Roth et al., 2019; Ahmad et al., 2017; Dedemen et al., 2017; Hsu, 2015), and cost analysis (Liu et al., 2020; Gao et al., 2019; Krstić & Marenjak, 2017; Au-Yong et al., 2014).

Maintenance work orders can be prioritized by collecting and providing access to necessary information. Developing data requirements in strategic, management and operations levels (Chanter & Swallow, 2008) and implementing data-driven decision-making methods can support consistent and continuous data collection, storage, and analysis to support existing challenges with user-driven decision makings. Such approach can improve the quality of the work performed.

Researchers have considered data analytics and ML implementation for addressing challenges related to the work order processing. Assaf et al. (2020) used machine learning algorithms to address predictive maintenance by analyzing occupants' complaint data. They implemented text mining to identify the most frequent complains of the occupants. Based on their results, complains related to air conditioner were among the most frequent complains. They then used ML to develop a model to predict the future complains in order to help FM professionals to plan ahead. Cao et al. (2015) developed a framework using artificial intelligence to prioritize work orders based on both occupants' and facility managers' feedbacks. Considering occupants' satisfaction and safety is among the criteria considered when processing work orders. Being able to draw conclusions from previous work orders can help with developing better plans with addressing future work orders.

Besiktepe et al. (2019) used historical work order data in educational institutions to identify the frequency of maintenance activities and explore possible relationship between building age and type and maintenance activities. Their study identifies the systems with highest maintenance frequency and their results indicate no relationship between building age and type and the maintenance activities. Yang et al. (2018) developed a failure mode and effect analysis (FMEA) method using data mining to address the HVAC maintenance issues. They used the work order data from building energy management systems. Based on their results, the analysis of work order data can help with determining parameters for FMEA models while it can also help with determining the high impact failures. Furthermore, their results indicate that there is a relationship between frequency of faults and building type. Determining the frequency of maintenance activities of an asset can impact the FM approach in different aspects including priority of the asset or the maintenance type. Furthermore, data analytics allow other determining factors impacting the process of work orders such as building type in order to provide a more comprehensive and practical solution.

Kolokas et al. (2018) used the data collected from sensors and implemented artificial neural network for detecting and predicting faults in industrial equipment. Their results support predictive maintenance. The ML classifiers used in their study allowed them to predict equipment failures five to ten minutes before the breakdown using the changes from the data collected by the sensors. Canizo et al. (2017) implemented random forest to their workflow to predict wind turbines failures to address predictive maintenance. Although their results presented an overall success in predicting failures, they believe that there is a need for accuracy improvement. Current predictive maintenances are mainly scheduled based on the recommendation of the manufacturer. Updating the predictive schedule based on actual performance of the assets supports higher quality of services provided by the facility. Additionally, being able to predict failures ahead of time allows avoiding downtimes which leads to less facility cost.

Lempert et al. (2016) implemented machine learning for prioritizing road repair tasks according to optimal utilization of resources. Their proposed solution is based on defect recognition and classification methods and allows prioritizing the future repair tasks based on their historical data. Abdelrahim and George (2000) implemented the neural network into the process of prioritization and selection of pavement maintenance strategy based on the level of alligator cracks, traffic volume, condition of the pavement, distress type, and road class. Collecting and storing data in consistent and continuous matter allows benefiting from historical data to support processing future work orders. Such approach accelerates processing work orders while allowing the system to update over time.

5.4 Methodology

To conduct this research, an application was submitted to the institutional review board (IRB) at Virginia Tech under the protocol number IRB- 20-879. According to the study objectives, IRB determined that the proposed activity is exempted for further review. The work order data from an educational facility was received, processed, and analyzed to develop the neural network model supporting the processing and prioritization of future work orders. Figure 5.1 presents the methodology steps taken to analyze and implement neural networks to the work order data received perform the educational facility and presents what has been addressed under each step.

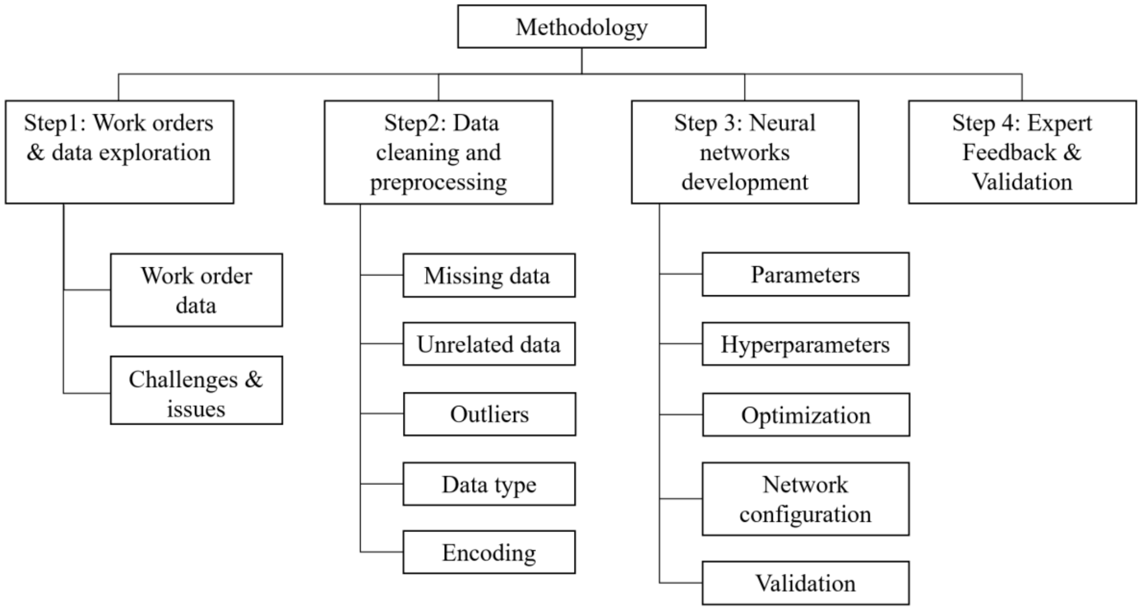

Figure 5.1. Methodology steps

Step 1: The work order data collected during the past eight years by an educational facility was received for this research. The data included the work orders and 12 criteria (Table 5.1) mostly populated in the facility system to support the processing of their work orders. The data received was explored to understand the data and identify any challenges associated with their data such as missing data. Data exploration is a significant part of the process of developing machine learning solutions in terms of understanding the data, addressing the data quality challenges, and preparing the data for development (Kelleher et al., 2015). The accuracy and quality of data impacts the training process as well as the performance of the machine learning model and its outcome (El Naqa et al., 2018). Furthermore, since the data generated by the developed ML models feeds back into the models to further develop and train the models, small accuracy error can lead to extreme deviations from real outcomes over time (Polyzotis et al., 2019). This highlights the importance of data quality during different stages of data preprocessing including data analysis (Hellerstein, 2008). Researchers have indicated that poor data quality has cost businesses in the United Stated about $700 billion annually since problems raised from data quality issues can lead to project failure and revenue lost (Gudivada et al., 2017). Examples of data quality challenges include missing value, extreme high value or outliers, wrong value, false and/or inconsistent values, false data type, and new feature identified (Kelleher et al., 2015; Krishnan et al., 2016; Polyzotis et al., 2019).

Step 2: Data cleaning and preprocessing were carried out on the work order data of an educational facility to address the identified challenges and prepare the data for model training. As part of this step, a first meeting was conducted with the facility to receive their input and opinion about parts of the data cleaning processing (e.g., removing outliers). Data cleaning and preprocessing was performed using Python libraries including Pandas (McKinney, 2011), Numpy (Van Der Walt et al., 2011), scikit learn (Pedregosa et al., 2011). Data cleaning is "the process of detecting and correcting errors in data" (Chu et al., 2013, p.458). The importance of data cleaning has been highlighted by different researchers (Volkovs et al., 2014; Schelter et al., 2018; Gudivada et al., 2017) as inconsistent and incorrect data can negatively impact the results. Models developed with faulty data will lead to unreliable decisions taking away the benefits of data-driven decision-makings (Chu et al., 2016). Data preprocessing is the steps taken to transform the raw data to a format that can be used and analyzed by machine learning. Examples of such steps include encoding or the selection of the features to be used by the machine learning model (Gao, 2012).

Data cleaning techniques can be categorized into two groups: quantitative and qualitative (Chu et al., 2016). Qualitative techniques use constraints, rules, and patterns to identify the errors (duplicates, misclassification, misspelling and typos) (Hellerstein, 2008). Examples of setting constraints include specifying a one-way relationship between two attributes (Harrington, 2016), defining a set of values that are valid for a feature such as data type (Calı et al., 2003), or indicating that the primary key value which is the identifier cannot be null (Huang, 2017). This technique was used when working with contextual data such as using work description and building names to fill in the missing data for latitude and longitude. This technique was also used to search through work description and removed unrelated work orders, search through completion dates and remove rows with empty cells and change the user values with categories of years of experience. The quantitative techniques use statistical methods such as probabilities, mean, or distribution for identifying the outliers, errors (e.g., duplication, incorrect or missing values), and abnormalities (Hellerstein, 2008). This technique was used for dealing with numerical data such as filling the missing values for hours and number of crews using medians. The quantitative technique was also used for determining and removing outliers based on the duration taken to address maintenance tasks and was used to identify the correlations between criteria used and the schedules. To address the data quality challenges identified, data cleaning and preprocessing was performed using Python libraries including Pandas (McKinney, 2011), Numpy (Van Der Walt et al., 2011), scikit learn (Pedregosa et al., 2011) libraries.

Step 3: The cleaned data was used to implement neural networks, determine the best configuration, and automate the prioritization of work orders. Recently, Artificial Neural Networks (ANNs) have become popular and useful for problem-solving in various fields. The ANNs models can be used for addressing pattern recognition, natural language processing, classification, prediction, etc. (Abiodun et al., 2018). Artificial Neural Network is one type of machine learning models which reflects and mimics the behavior of the human brain to understand the relationship between a set of data allowing computer programs to solve complex data-driven problems (Abiodun et al., 2018; Wang, 2003). Neural networks can learn from modified inputs the need for redesigning the criteria and framework providing the most efficient and practical solution without manual modification (Abiodun et al., 2018).

First, 20 percent of the data was separated to be used for validation after training and testing the data. This approach is used to isolate a subset of the data on which model validation is performed with the same input condition (Duval, 1992). Using the Scikit learn library in Python, the remaining 80 percent of the cleaned data was randomly divided into training (64% of the total data) and test set (16% of the total data) in order to develop the neural networks model. An initial network architecture was chosen to start the training process. The TensorFlow (Abadi et al., 2016) and Keras (Chollet et al., 2015) libraries were used for developing the ANN model by determining the number of nodes for the hidden layers and changing the model hyperparameter (e.g., learning rate, distribution) to determine the best values for the model. As shown in Figure 5.2, neural network models consist of three sections: input, hidden, and output layers of neurons or nodes. The input layer represents the predictive features. The hidden layer represents an aggregation of information from input data. The more nodes included in the layers; the more interactions will be captured which finally impact the results (output layer). The connections between neurons are called edges and are associated with the numerical values of weights which indicate how strong a layer/node impacts the next layer/node.

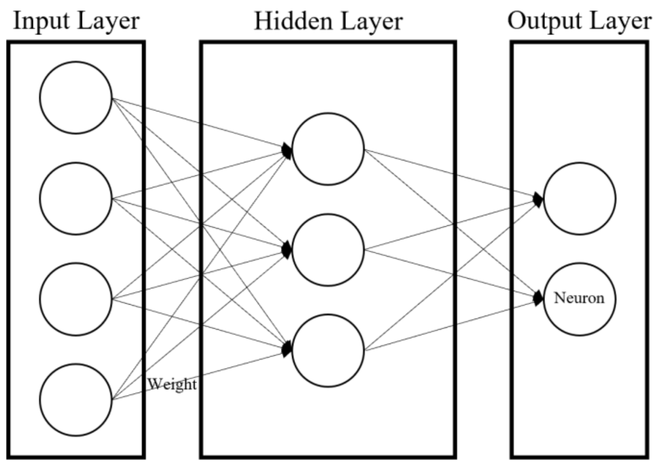

Figure 5.2. General neural network model

For model training, the model takes the criteria (features) and their associated values as input and uses the duration taken from the date the work order is created until the date the maintenance task is completed as the output (expected result). Through the training, the model estimates the weight of each input in the hidden layer/s based on the outputs (Figure 5.3). Depending on the needs of the model, the hidden layer consists of one or more layers performing transformation on their input. The mean squared error was selected as the metric or loss function to obtain the best hyperparameters determining the best network configuration and supporting the performance of the model. The neural network starts with assigning random weights in the hidden layer to predict the output. Then the error indicating the difference between model's output (output layer) and previous recorded outcomes is calculated. The goal of the training model is to minimize that error by adjusting the weight of the edges connecting different neurons. To do so, backpropagation method is used to divide the error between the connections (Wang, 2003). The training of the neural network can be either based on the desired number of iterations or the desired error level.

After training the model, the test set would be given to the model and the output would be estimated by finding the sum of the weighted inputs. Through the test set, the accuracy of the model is estimated by comparing the results of the test and training sets. As this research only has access to one database, the 20 percent of the same database separated at the beginning was used as new data to validate the developed model using the results of mean squared error.

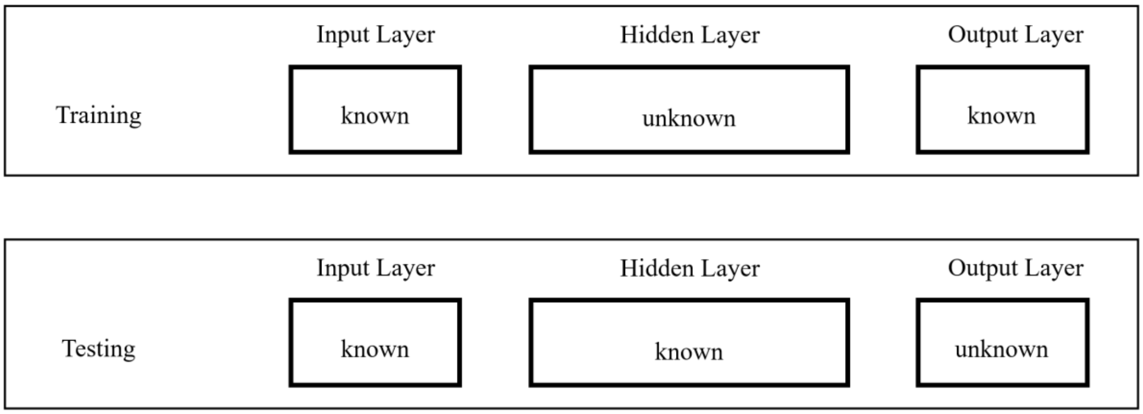

Figure 5.3. Training and test process

Step 4: A second meeting with three facility experts in the area of building operation and maintenance from the educational facility was conducted to first receive feedback regarding the insights gained from data exploration, cleaning, and preprocessing, and second validate the results of the developed neural networks model. This approach allows the facility expert to provide a shared opinion while providing feedback on a proposed model that deals with their daily practices adding to the insights of using ML models. The discussion was conducted through videoconferencing (zoom online meeting) and took about an hour. First, the results of data preprocessing, correlations determined, the parameters (features) used for this study, and the challenges with data preprocessing were discussed with the facility professionals to receive their opinion on the process and results. Second, the time that takes a facility staff to process 50 work orders (as they receive 50-70 work orders per day) was compared to processing time of the model and was discussed with the facility experts to measure the efficiency of the proposed approach. Third, the result of the 50 prioritized work orders performed by a facility staff was compared to the results of the model prioritization to determine the accuracy of the model. In the final step, the facility professionals were asked to provide feedback and discuss the advantages and disadvantages of using the model for prioritization.

5.5 Step-1: Work Orders and Data Exploration

The work order data of an educational facility was used to explore and process the work order data (Figure 5.4) and implement neural network for future work order processing. The educational facility has 213 buildings covering offices, classrooms, dining services, dormitories, laboratories, students' activity complexes. The buildings' area ranges from 685 sq ft to 418000 sq ft. The facility uses an in-house software for receiving the work orders and the work orders are processed and prioritized manually by the staff.

Total of 333436 work orders were received from the educational facility. The data collected from the facility covers the work order data from the past eight years (2014-2021). The facility receives approximately 50 to 70 maintenance requests per day on average (depending on the day and season). Based on the discussion with the facility as well as prior research described in chapters 3 and 4, 12 criteria (Table 5.1), mostly used and populated in the facility system, were requested from the facility for the development of the neural network model. To consider the possible impact that years of experience had on the decision-making process, one of the selected criteria was the user who processed the work orders. Table 5.1 provides the description of the data received from the facility as well as the data type for each criterion.

Clerk	Date created	Order type	Category	Craft	Shop	Maintenance Type	Work Description	Building Type	Latitude	Longitude	Labor	Total hours	Date completed
ENTCLERK76	2014-09-29 7:35:10 AM	OP	PM	PM	PREVENTATIVE MAINTENANCE	4-SCHEDULED	SEMI ANNUAL SERVICE OF FUME HOOD EXHAUST FANS IN XXX	GENERAL PURPOSE BUILDING	Latitude 1	Longitude 1	1	7.82	2014-10-30 2:12:39 PM
ENTCLERK76	2014-09-29 7:35:11 AM	OP	PM	PM	PREVENTATIVE MAINTENANCE	4-SCHEDULED	SEMI-ANNUAL SERVICE OF EXHAUST FANS IN XXX BUILDINGS WITH PM COVERAGE	GENERAL PURPOSE BUILDING	Latitude 2	Longitude 2	2	0.44	2014-10-30 2:17:30 PM
ENTCLERK14	2014-10-15 7:48:15 AM	OP	CM	EL	ELECTRICAL	3-ROUTINE	XXX - NO POWER TO DOMESTIC HOT WATER PUMP	GENERAL PURPOSE BUILDING	Latitude 3	Longitude 3	3	6.64	2014-11-20 4:29:02 PM
ENTCLERK14	2014-10-15 7:54:36 AM	OP	CM	EL	PREVENTATIVE MAINTENANCE	3-ROUTINE	XXX 441A - LIGHT OUT IN MECHANICAL ROOM NEAR BOILERS	GENERAL PURPOSE BUILDING	Latitude 4	Longitude 4	3	4.35	2014-10-21 10:58:26 AM
ENTCLERK14	2014-10-15 8:05:41 AM	OP	CM	DOOR MAINTENANCE	PREVENTATIVE MAINTENANCE	3-ROUTINE	XXX - 3RD FLOOR DOOR NOT CLOSING PROPERLY, BOLTS CAME OUT OF CLOSER IN THE STAIRWELL.	GENERAL PURPOSE BUILDING	Latitude 5	Longitude 5			2014-10-16 6:48:00 AM
ENTCLERK39	2014-10-15 2:23:12 PM	OP	CM	GR	GROUNDS	3-ROUTINE	XXX- PLEASE REMOVE METAL POST WHERE TREE WAS CUT DOWN AT GRAVEL PARKING LOT ON LEFT IF COMING UP FROM DUCKPOND	AUXILIARY SERVICES	Latitude 6	Longitude 6	3	1.5	2014-10-20 8:57:58 AM
ENTCLERK39	2014-10-15 2:33:37 PM	OP	CM	HVAC	REFRIGERATION	3-ROUTINE	XXX-300 TOO HOT	GENERAL PURPOSE BUILDING	Latitude 7	Longitude 7	4	14.2	2014-10-24 2:32:51 PM
ENTCLERK14	2014-10-15 3:16:50 PM	OP	CM	ELEV	ELEVATOR	2-URGENT	ELEVATOR REPAIR - ELEVATOR IN FRONT LOBBY NOT WORKING.	GENERAL PURPOSE BUILDING	Latitude 8	Longitude 8			2014-10-17 2:13:14 PM
ENTCLERK88	2014-10-15 3:26:13 PM	OP	CM	RO	ROOFING	3-ROUTINE	XXX-OUTSIDE 3320--WATER CAME THRU THE PORT. SHOWS FRESH DISCOLORATION AND SOME BUBBLING.	GENERAL PURPOSE BUILDING	Latitude 9	Longitude 9	7	26.96	2015-01-06 1:44:46 PM

Figure 5.4. Example of data received

Table 5.1. Headers' description

Header/criteria	Description	Data Type
Clerk	User who processed the work order. This column has later been transformed to years of experience of staff including small (below 2 yrs), medium (2-5 yrs), and high (over 5 yrs)	Categorical
Date created	The date and time the work order is entered into the system. Date and time when the work order is started is not known and is not tracked.	Date
Order type	Indicates the type of funding	Categorical
Category	Reflects a different categorization of maintenance type (e.g., corrective, preventative, renovations)	Categorical
Craft	Describes the shop responsible for addressing the work order (e.g., electrical, carpentry, elevator)	Categorical
Shop	The category of the work order (e.g., electrical, mechanical services, building trades, housekeeping)	Categorical
Maintenance Type	Describing the type of maintenance (e.g., scheduled, routine, urgent)	Categorical
Work Description	Short description of the work order	Textual
Building Type	The type of building (General Purpose Building, Academic/ Residence Building, Auxiliary Services, Physical Plant Building, Agriculture Services building, Single/Family Residence, Rental Property)	Categorical
Distance (Latitude/Longitude)	Distance from the main facility office (calculated using latitude and longitude)	Numerical
Labor	Number of labors for performing the maintenance task	Numerical
Total hours	The amount of time taken to perform the maintenance task	Numerical
Date completed	The date and time the work order (maintenance) is completed.	Date

The work order data received from the facility was further explored to understand the data and the features, determine irrelevant information, and identify challenges such as missing data and typos in order to address them. Data exploration was conducted by search through different columns to determine the empty cells, searching keywords in the work description column, and categorizing the rows based on a value for a specific column. Through exploring the work order data received, the following challenges were identified:

- Data included irrelevant work orders (e.g., work orders related to football fields, roads, bus stops) which needed to be removed.
- The “date completed” column had missing data. As this column covers the target for the machine learning model, the rows with missing data needed to be removed.
- The “Building Type”, “Distance”, “Labor”, and “Total Hours” columns also had missing data.
- Some buildings had been demolished which needed to be removed from the list as they did not exist anymore.
- In some cases, instead of mentioning the location of the work order, the name of the facility staff which had the area assigned to them, was included in the descriptions. For instance, the requestor had entered “All my buildings” instead of the building name or the work order indicated “Inspect buildings in XXX’s area”.
- Some work orders included in the database were not actual work orders. They only covered discussions between facility staff such as pointing out an upcoming meeting.
- A few work orders included region number which was not discussed anywhere in the facility system.
- In few cases, multiple work orders were requested as one work order making it complicated to track resources, time, and labor.

5.6 Step-2: Data Cleaning and Preprocessing

The qualitative and quantitative methods were used to clean and prepare the data for implementation of neural networks. With reference to the third column in Table 5.1, the qualitative techniques were used when working with textual and categorical data and quantitative techniques were used for addressing numerical data. Both qualitative and quantitative techniques were used to prepare the data. Figure 5.5 presents the techniques used and steps taken to clean and preprocess the data.

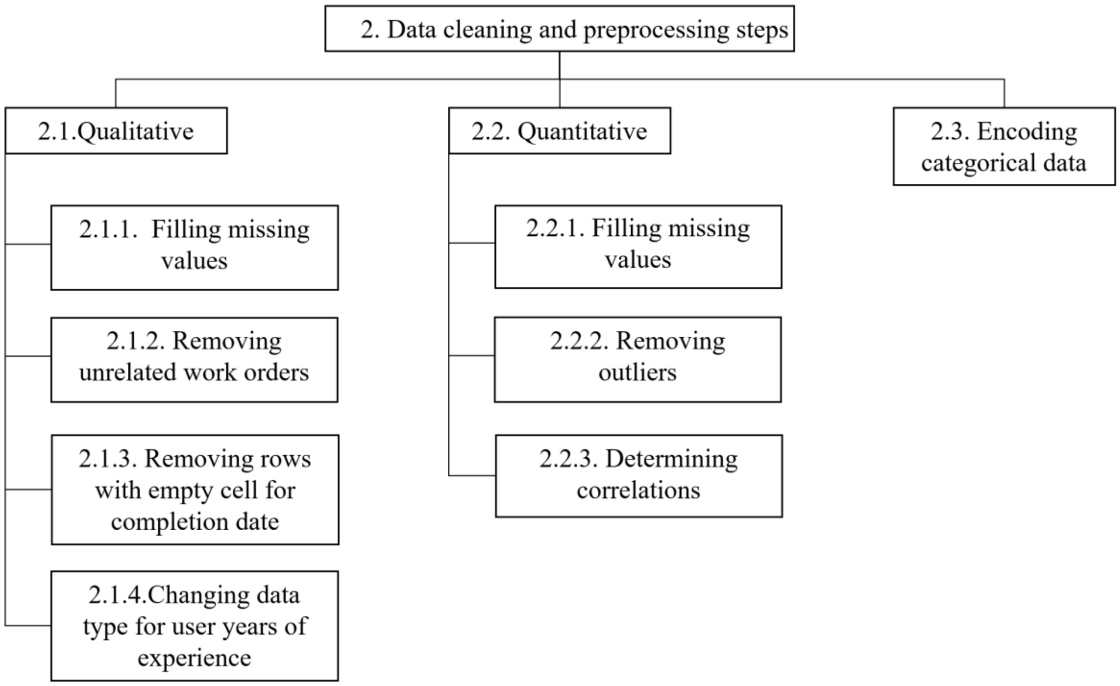

Figure 5.5. Steps taken for preparing the data

For this research, the qualitative technique (Figure 5.5, step 2.1.) was first used to fill the missing values (Figure 5.5, step 2.1.1.) for “building type”, “latitude”, and “longitude” columns. To do so, the list of campus buildings was collected from the facility website which included the abbreviation and full name description for each building. The “Work Description” column in the work order database contained the building name or the building abbreviation. By using the exported list of building names and applying text mining code on the “Work Description” column, the building name or abbreviations were searched and identified in the description to fill in the missing values in building type, latitude, and longitude (distance) columns based on work orders associated with the same building which had a value for the mentioned columns (Pseudocode 5.1).

```
List1 = [ Building ID, Latitude, Longitude] for all buildings
Object ID = [ Building ID | Non-Building-info]
Work Order Description = Object ID + Descriptive Information
List2 = [ Work Order Description] for all Work Orders
List3 = Work Orders containing Building ID in List2
For each "Building ID" in List3:
Do
Find the member containing the same "Building ID" in List1
        Get the associated Longitude and Latitude for that list member
        Append the extracted Longitude and Latitude to List2
Done
```

Pseudocode 5.1. Filling missing values

The next step was to remove unrelated work orders (Figure 5.5, step 2.1.2.). Work orders containing the following keywords: purchase, road, bike rack, bus stop, seed, grass, sidewalk, and tree, were removed from the database as they were not addressing building operation and maintenance (Pseudocode 5.2).

```
Object ID = [ Building ID | Non-Building-info]
Work Order Description = Object ID + Descriptive Information
List2 = [ Work Order Description] for all Work Orders

For each Work Order of List2:
Do
        If Work Order contains Non-Building-info:
                Delete Work Order
Done
```

Pseudocode 5.2. Removing unrelated work orders

The "date completed" column was an important part of the database due to its significance in estimating the schedule and prioritization of the tasks performed which was used as the target column for the machine learning model. It was important to remove rows (Figure

5.5, step 2.1.3.) with missing value for this column. The qualitative method was then used to remove the rows with empty cells for this column.

The" clerk" column included the unique value for each facility staff processing work orders and needed to be changed to meaningful information (Figure 5.5, step 2.1.4.). The qualitative method was used to change the numerical values for the "clerk" to categorical values (Pseudocode 5.3). The academic facility divides its staff into three categories based on their years of experience. After addressing all the missing data, the values for "clerk" column entered into the system was used to replace the values with one of the three categories (levels) of small (below 2 years), medium (2-5 years), and high (over 5 years) years of experience.

```
List1 = [ Clerk ID, The Range of Years of Experience] for all clerks
List2 = [ Clerk ID, Work Order Description, Other Work Order Info ] for all Work Orders
For each "Clerk ID" in List2:
Do
Find the member containing the same "Clerk ID" in List1
        Get the associated Years of Experience for that Clerk ID in List1
Replace Clerk ID in List2 with the extracted Years of Experience
Done
```

Pseudocode 5.3. Replacing clerk information

The quantitative technique (Figure 5.5, step 2.2.) was implemented for further data cleaning. It was first used for addressing the remaining missing data (Figure 5.5, step 2.2.1.) and second, was used for removing the outliers based on the maintenance type (Figure 5.5, step 2.2.2.). Although some missing values were addressed using the qualitative method, the database still had missing values for "labor" and "total hours" which needed to be filled. The quantitative method was first used to simulate the missing data for "labor" (number of labors involved) and "total hours". Using the rows filled with data, the data was grouped based on "Order Type", "Category", "Shop", and "Maintenance Type" (Pseudocode 5.4.). These specific four factors were chosen based on the recommendation of the facility experts from the educational facility as they believed that rows with similar values for the four mentioned criteria can be used to simulate the labor and total hours. In other words, the values for labor and total can be almost similar when the values for the four parameters mentioned above are the same. About two percent of the data was removed as the entire category did not include any value for the labor and total hours columns. For the remaining data, the median value of each category was used for filling the missing cells. Using median instead of mean reduces the possible impact of any outlier.

```
List1 = ['Work_order_Number', 'Order_Type', 'Category', 'Shop', 'Maintenance_TYPE', 'Number_of_Labors'] for all work orders

MetaData = Order_Type + Category + Shop + Maintenance_Type

List2 = [list of (GRP, MED) pairs] #Placeholder for Work Order Groups with similar MetaData (GRP), and associated Median number of Labors (MED).
For each work order in List1 that contains 'Number_of_Labors':
Do
Compare the MetaData for the current Work Order with the rest of the work orders in List1
MED = Median of the Number_of_Labors for all Work Orders with the same MetaData
GRP = [ list of Work Orders with the same MetaData]
Add (GRP, MED) to List1
Done

For each (GRP, Med) pair in List2:
Do
        For each work order in List1:
        Do
                If MetaData for GRP = MetaData for current work order in List1:
                        IF Number_of_Labors is empty:
                                Number_of_Labors = MED
        Done
Done
```

Pseudocode 5.4. Filling remaining missing data

After filling the missing data, the remaining data was explored as it is important to remove outliers from the database (Figure 5.5, step 2.2.). Outliers are datapoints that greatly differ from the rest of the data, and they can skew the final results. Based on the maintenance type (e.g., scheduled vs. emergency), the work order schedule estimated using the date created and date completed, was explored to identify outliers impacting the output column.

Based on the recommendation of the facility experts, maintenance type was selected as a reference for determining the outliers as there should be a limitation in terms of how long the shops can take to address each maintenance type. The maintenance types were divided into four categories of emergency, urgent, routine, and scheduled. The following presents the definition of each category:

1. Emergency: immediate action required (e.g., security issue, life safety, life threating loss of research in a lab
2. Urgent: 24 to 48 hours response needed. (e.g., lights out, door not functioning, plumbing concerns)
3. Routine: one week response needed (e.g., replacement of ceiling tiles, HVAC filters)
4. Scheduled: should be addressed on specific date or month (e.g., fume hood)

The duration taken for addressing each work order was calculated based on the date the work orders were submitted and the date on which the work orders were completely addressed. Given that the actual start date to perform each work order is not known (the educational facility does not track the date), it was assumed that the date and time the work order is entered into the system (Date Created) is the starting date/time of the work order. After determining the duration of the work orders in each category, the results were translated to Figure 5.5 and Table 5.2 and were discussed with the facility experts to determine the outliers based on the durations. Figure 5.6 and Table 5.2 summarizes work orders by maintenance type, duration to complete work orders divided into 5 duration categories and the number of work order in each duration category.

Based on the discussion with the educational facility and according to their practices, both 90 and 95 percentiles of each maintenance type were exported to be used for the machine learning model. Table 5.3 presents the maximum duration for each maintenance category. Work orders that took longer duration to be addressed were removed as they were counted as outliers by the facility. It is important to highlight that although a maintenance has been marked as urgent in the system, the time taken to address the maintenance may take longer than what is expected for such maintenance type depending on the issue identified and the resources needed for addressing the issue. The results of the 90 (283,325 rows) and 95 (299,065 rows) percentiles would be compared to select the best percentile in terms of model performance.

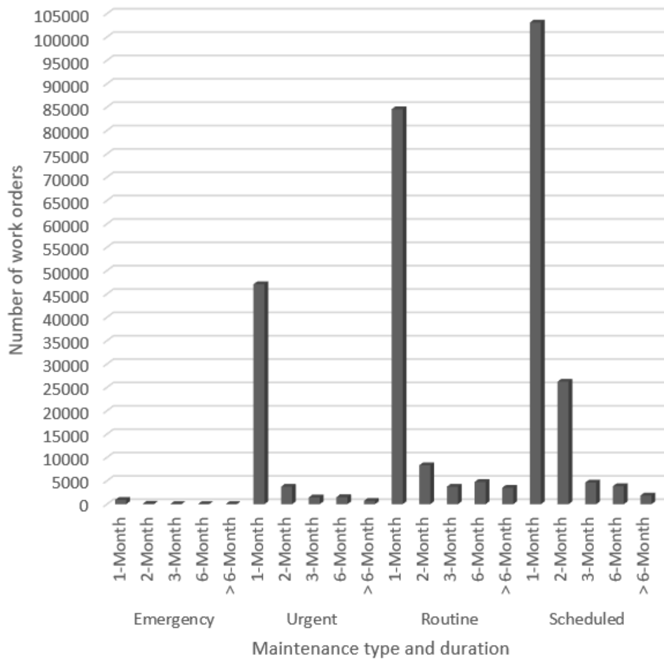

Figure 5.6. Number of work orders addressed for each maintenance type in the educational facility

Table 5.2. Number of work orders addressed in each duration

Maintenance type	Duration (Days)	Number of work orders
Emergency Total work orders: 1,131	<=30 Days	932
	30-60 Days	104
	60-90 Days	37
	90-180 days	42
	>180 days	16
Urgent Total work orders:54,493	<=30 Days	47,083
	30-60 Days	3,748
	60-90 Days	1,442
	90-180 days	1,502
	>180 days	718

Routine	<=30 Days	84,551
	30-60 Days	8,334
Total work orders:104,903	60-90 Days	3,744
	90-180 days	4,750
	>180 days	3,524
Scheduled	<=30 Days	103,107
	30-60 Days	26,229
Total work orders:139,663	60-90 Days	4,619
	90-180 days	3,848
	>180 days	1,860

Table 5.3. Duration used for removing outliers

Maintenance Type	Percentile kept	Duration (number of days)
Emergency	0.95	92
Urgent	0.95	77
Routine	0.95	140
Scheduled	0.95	79
Emergency	0.90	47
Urgent	0.90	42
Routine	0.90	76
Scheduled	0.90	57

In the final step of the data cleaning, the quantitative technique was used to understand the correlation between different parameters (features) in the database (Figure 5.5, step 2.3.). The correlation between different features included for the model was explored to make possible interpretations after the machine learning analysis. The correlations were estimated using the Dython library in Python (Dython, n.d.).Figure 5.7 presents the heat-map of correlations highlighting shop, craft, and category as parameters with the highest correlation with schedule (duration).

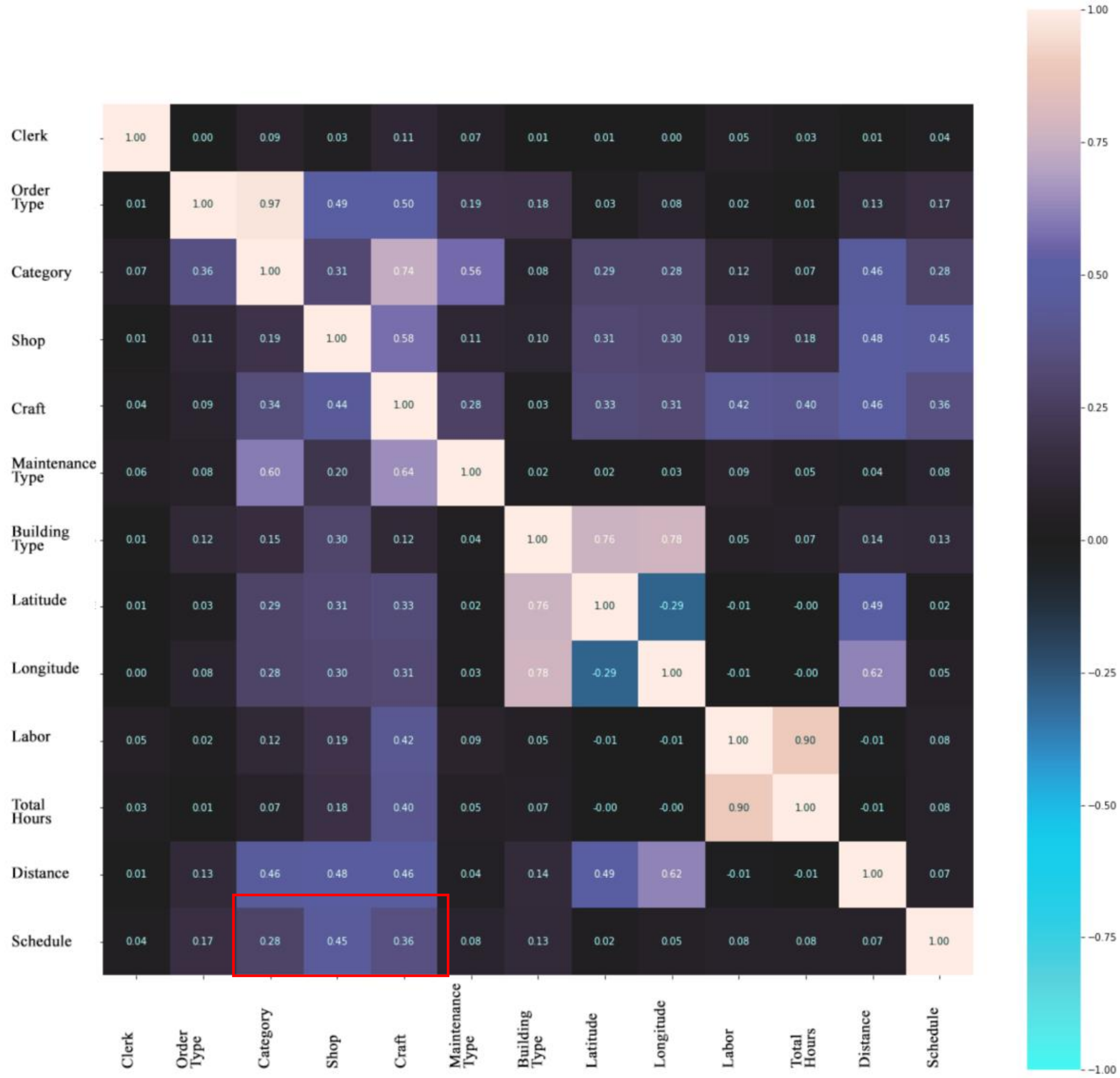

Figure 5.7. Correlation between different parameters

After finalizing the database, “onehotcoding” from “sklearn” library was used to encode the categorical data (Figure 5.5, step 3). Onehotcoding turns the categorical data into multiple columns with each class being included in one column. It creates binary vector for each class removing the impact of numerical orders. For instance, if the building type has three types of A, B, and C, the building type column will be divided into three columns of Building A, Building B, and Building C. Value 1 indicates that the work order has that building type.

Table 5.4. Encoding categorical data

Work Order	Building A	Building B	Building C
Work Order 1	1	0	0
Work Order 2	0	1	0
Work Order 3	0	0	1

Before using the data for neural networks, the dataset had to be normalized (Appendix C) to create the same scale (ranging from 0 to 1) for all inputs and features. This technique helps when the database has features with different numbering scales. In this research, MinMaxScaler (sklearn library) was used to normalize the data.

5.7 Step-3: Artificial Neural Network Development

After preprocessing and separating a set of data for validation, the remaining data was divided into a training set and a test set (train-test split). However, this method creates noisy results because of the randomness of the data and the stochastic nature of ANNs. In order to address the randomness of data (receiving different results when same model is trained on the same data) the same randomness (seed=7) was specified. Specifying a number for seed keeps the starting point the same and supports receiving consistent results when the model is trained on the same data again.

As discussed previously, the neural networks contain multiple layers including one input layer, one output layer, and one or more hidden layers. To perform the training, part of the criteria received from the facility (Figure 5.8, input) were used as features for the input layer of the model. The dates received from facility were used to estimate the duration by subtracting the two dates and times. The duration was used for the model output layer (Figure 5.8, output) for two main reasons. First, since the facility does not collect other dates associated with the work orders including the actual maintenance start date or the diagnostic duration. Second, based on previous discussions with the facility experts regarding their manual work order processing, it was identified that work orders with less distance or quick work orders were scheduled with higher priority as they could be addressed faster and be removed from the list. Therefore, it was assumed that the duration is the best feature that can be used considering what is collected by the facility and is stored in the database as well as considering their manual processing practices.

Input											Output	
Clerk	**Order type**	**Category**	**Craft**	**Shop**	**Maintenance Type**	**Building Type**	**Latitude**	**Longitude**	**Labor**	**Total hours**	**Date created**	**Date completed**

Figure 5.8. Input and outputs of the model

Through the training process, the model uses the features (criteria) and their values to estimate the weight for each feature in the hidden layer/s and determine the significance of their impact on the duration/output (expected result). This is done by first assigning random weights to the neurons in the hidden layer and adjusting the weights using a loss function. A desired loss function, in this case mean squared error, is used through this process to adjust the estimated weights by minimizing the difference between estimated and actual output (duration). After training the model and determining the best network configuration, the test set is used to compare the results of the mean squared errors and ensure that the test set provides results that are close to results of the training model.

5.7.1 Development of the Neural Network Model

The TensorFlow (Abadi et al., 2016) and Keras (Chollet et al., 2015) libraries in Python were used to design and create the neural network model in order to train and test the data. Through creating the model, the number of nodes for hidden layers were determined, the values for hyperparameters were defined, and the activation function (relu and sigmoid) and optimizer (adam) were selected. After compiling the model, the KerasRegressor was used to convert the model to a scikit learn (Pedregosa et al., 2011) model to be able to optimize the model using GridSearchCV. The following sections provide the details of these steps (Figure 5.9).

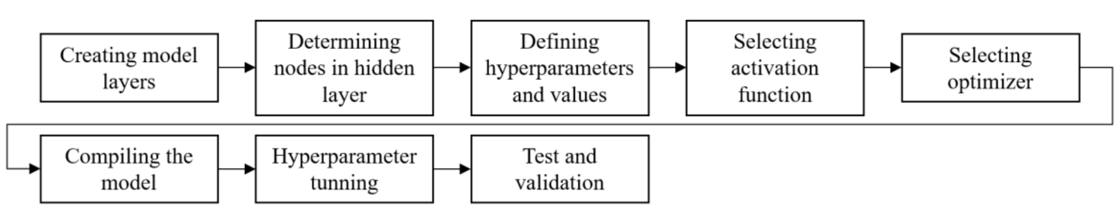

Figure 5.9. Steps taken to develop and test the model

The size of the network depends on the number of nodes, the width depends on the number of nodes in a layer, and the depth describes the number of layers in the network. Although some literatures have counted one hidden layer as sufficient for approximation of most functions (Goodfellow et al., 2017), others have argued that one hidden layer is not sufficient or not as efficient as having multiple layers for all functions (Reed & MarksII, 1999). A sequential multiple-layer network or Multilayer Perceptron (MLP) was used as more than one layer was required for a multi-dimensional (multiple features) problem. The MLP constitutes a sequence of layers containing an input layer, one or more hidden layers, and an output layer. An important aspect when choosing a sequential MLP model is determining the number of hidden layers and the number of nodes in each layer.

First, the number of nodes for the hidden layers were determined using the number of nodes in the input and output layers. In the next step, a function was defined to vary the model hyperparameters in order to determine the best values for the model values as they control the training process. As opposed to parameters which are learned through the training process (e.g., weights), hyperparameters are the properties that should be determined and set prior to training as they are not learned through the process. The function defined changes the value for five hyperparameters of number of nodes in the first layer (number of features), number of samples per gradient update, learning rate (how quickly the parameters are updated by the network), distribution, and the total number of layers (input, hidden, and output layers). The following presents the values tested for each mentioned hyperparameter.

- First layer nodes' range: (55, 195, 10)
- Batch Size: [32, 64, 128, 256, 512]
- Learning rate: [0.005, 0.01, 0.1, 0.2, 0.3]
- Distribution: ['uniform', 'normal']
- Number of layers: [3, 4, 5, 6, 7]

In the next step, an activation function was selected. Activation functions determine how the weighted sum of the input is transformed into an output. The “Relu” activation function was used for input and hidden layers as it adds nonlinearity to the data allowing adaptation to a wide range of data. The “Sigmoid” activation was used for the output layer since this problem is dealing with regression and not classification.

There are multiple algorithms including gradient descent and adagrad that can be used for optimization of neural network training. Optimizers are used to reduce the losses of the machine learning models by changing attributes such as learning rate. the “Adam” optimizer was used for this research as it is more efficient in terms of memory use when working with large amount of data leading to more efficient training in less amount of time. “Adam” uses first and second gradient moments for estimating the individual adaptive rates of different parameters (Kingma & Ba, 2015). Adam optimizer combines two gradients of momentum and root mean square propagation. The momentum is based on exponentially weighted average of the gradients to increase the pace (Appendix B, equation (1)). Root means square prop is based on exponential moving average (Appendix B, equation (2)). The Adam optimizer benefits from the two gradients to be able to take big steps while maintaining minimum oscillation reaching the global minimum. Such approach positively impacts the time and training performance (Appendix B, equation (3)).

5.7.2 Model Optimization

Hyperparameter tuning or hyperparameter optimization was used to identify the optimal number and arrangement of hyperparameters discussed in the previous (e.g., learning rate and number of iterations for gradient descent, number of layers and neurons for the ANN) section to achieve the best performance. Such approach can increase model performance, maximize accuracy, and/or minimize errors. There are multiple algorithms that can be used for optimization, such as random, grid, and exhaustive search. Random search is good for identifying new hyperparameters values, but the processing takes more time. The random search uses random numbers to find the best score for a combination of hyperparameters. Exhaustive search tests all combinations and is therefore useful for small datasets as it has long processing time. For this model, the grid search (GridSearchCV imported from scikit-learn library in Python) which performs a systematic search using different number of layers and nodes per layer was selected. The grid search defines the space as a grid of hyperparameter values and every position in the grid is evaluated to identify the best vector in terms of model performance. The following are the arguments of the GridSearch:

1. Estimator which is the model instance
2. Scoring is the objective/metric/lost function which in this case was the negative mean squared error as it is the default loss function for regression models and is typically used for neural network models. This loss function calculates the average of squared difference ($\frac{1}{n}\sum_{i}^{n}\left(y_i - \hat{y}_i\right)^2$) between actual (duration in the system) and predicted values (calculated duration). The goal of our model is to minimize the value for this hyperparameter and get the lowest score.
3. Cross validation (CV) was set to two as this research contained high amounts of data reducing the need for cross validation.
4. N-jobs for using the CPU cores in parallel which in this case the researchers selected 1 to use one CPU core.
5. Refit which refits the estimator based on a parameter.
6. Verbose is related to the messages presented.

5.7.3 Model Results

In order to determine the best configuration for the neural network, the development process tests different combinations of hyperparameters (Table 5.5) in terms of their values to achieve the least mean squared error supporting the accuracy and performance of the model. The best configuration was selected based on the value of the mean squared error estimated. There is no correct value for mean squared error, however, a lower value for mean squared error presents closer prediction to the actual value. As discussed in section 5.7.2, the mean squared error calculates the average of squared difference between actual and predicted values (actual and predicted duration) and the goal of the model is to get the minimum value to achieve the most accurate result through the model. Table 5.5 presents other combinations of the hyperparameters' values. By comparing Table 5.5 to Table 5.6, it is clear that different combinations of hyperparameter values had led to different mean squared error values. Through model training and by testing different combinations of the hyperparameter values, the model identified the optimum value for each hyperparameter in order to achieve the minimum mean squared error.

Table 5.5. Results of other combinations of hyperparameters

batch_size	first_layer_nodes	init_mode	learning_rate	n_layers	mean_squared_error
32	105	uniform	0.1	4	0.415344
512	75	uniform	0.01	3	0.016354
32	55	uniform	0.1	4	0.034170
128	185	normal	0.01	3	0.015893
64	135	normal	0.1	6	0.415344
64	75	uniform	0.3	3	0.034170
64	185	normal	0.005	3	0.015938
128	185	normal	0.2	3	0.034170
128	75	normal	0.3	6	0.414476
256	55	normal	0.2	4	0.034170
512	145	normal	0.01	3	0.029696
32	85	normal	0.005	7	0.034170

Table 5.6 presents the results of the optimal model performance score (mean squared error) and best values for the hyperparameters. As mentioned above, both the 95 and 90 percentile data were tested to identify the best dataset to continue with. The following presents the results for both databases.

Table 5.6. Results of the ANN model

Dataset	Mean squared error	Batch size	First layer nodes	Distribution	Learning rate	Number of layers
95 Percentile	0.016310	128	195	Normal	0.005	3
90 Percentile	0.025804	256	185	Normal	0.005	3

Based on the results, the 95-percentile database was selected for testing the model. The hyperparameters values of the 95 percentiles were used for the model to run the test set. The results of the test set presented the value of 0.01631 for the mean squared error which does not vary greatly from the training set result. As discussed previously, 20 percent of the data was separated before splitting the data for training and testing to be able to validate the model using new data. The mean squared error estimated from the validation dataset was 0.069147. Figure 5.10 presenta a comparison of the results of the developed model and actual data in terms of work order prioritization. As it is shown, a work order prioritized as first was prioritized as 13 by the model as it is based on multiple data entry over a long period of time.

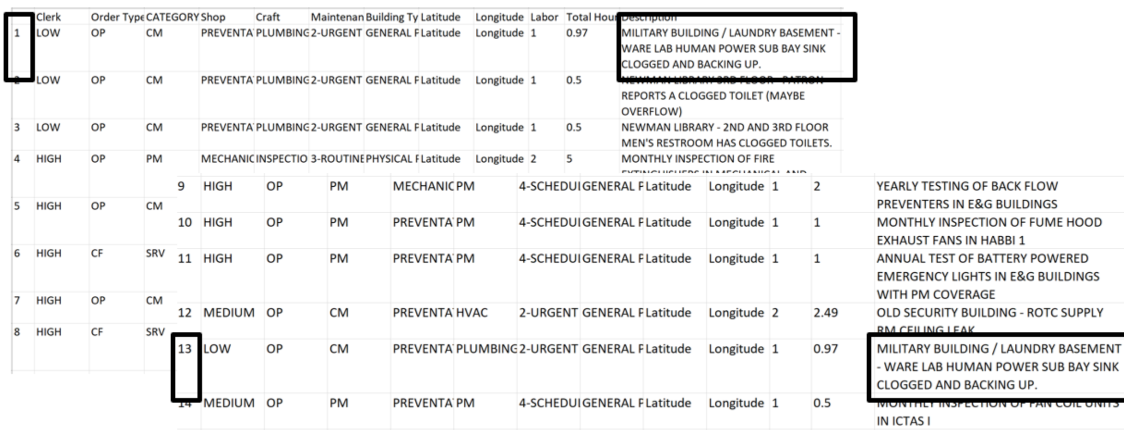

Figure 5.10. Comparison of actual and model prioritiztion

To be able to further validate the developed model and adjust the parameters and hyperparameters if needed, the developed model should be validated using a completely new dataset.

5.8 Step-4: Expert Feedback & Validation

As discussed in the challenges associated with existing practices for processing and prioritizing work orders, the existing practices take long amount of time and are prone to errors. Additionally, the criteria and their associated ranking used for processing work orders vary among different individuals within the same facility as well as among individuals in different types of facility. Therefore, the objective of this study was to propose the implementation of neural networks to automate the process of prioritizing work orders in order to address the following goals. First, enhance efficiency of the work order prioritization in terms of the amount of time taken to process and prioritize them. Second, to improve the accuracy in terms of accuracy of the prioritization and ranking of the work orders. Third, to increase the consistency in terms of criteria used for prioritization of the work orders as well as their associated ranking.

In order to address the goals of the study, the final results were discussed with a group comprised of three facility experts working in the same facility that provided the work order data to receive their opinion and feedback on the practicality of the proposed approach and evaluate the accuracy and efficiency of the proposed model. The efficiency was measured by comparing the time taken by the model as opposed to time taken by a facility staff to process and prioritize the work orders. The accuracy of the proposed model was evaluated by comparing the results of 50 prioritized work order by the model as opposed to prioritization of the same set of work orders by the facility. Finally, the consistency in terms of criteria used for prioritization was discussed with the facility experts to confirm that using the same criteria by the proposed model will increase the consistency of their process.

In the first step, the facility experts were asked to provide feedback on insights gained from data exploration, correlations identified, and the challenges with data preprocessing which were related to how the data is being collected and stored by the facility. Using data exploration, multiple challenges including missing data for multiple columns, using facility staff name who have an assigned area instead of the location name, or submission of the discussion among facility staff as work orders were identified. Based on the discussion with the facility staff, lack of requirements and guidelines have led to inconsistency in terms of data collection and entry which hinders benefiting from the data collected in terms of data-driven decision-making methods. Based on their feedback, data exploration and analysis can assist them with monitoring procedures and can help them to address the challenges with future data collection by defining guidelines and requirements. For instance, based on the results of Figure 5.6, the facility experts believed that defining requirements and performing follow ups can help with addressing the maintenance tasks in an acceptable amount of time while ensuring that the maintenance tasks have been closed. Such analysis can also help them to determine other criteria such as staff availability to better support their processing procedure. Furthermore, they believed that such analysis could help with redefining some criteria (e.g., changing a maintenance task category from urgent to routine) while evaluating the performance of the staff and any challenges faced by them in order to address them for future processes.

The facility experts indicated that work order data analysis can also assist them in determining what specific fields should be captured, what data should be collected through the description to better determine the type of the issues, and how and when to perform follow ups. Based on correlations determined in Figure 5.7, the facility experts believed that analyzing information used for processing work orders and determining their correlation and impact on prioritization and schedule can assist them in determining data requirements. In other word, if the facility is collecting data for a criterion such as distance which has little impact on the schedule as opposed to assigned shop, they should avoid spending resources to collect data for such criterion and replace the criterion with other beneficial criteria enhancing their practices. They also indicated that these types of analysis can help with determining better practices as well as providing an opportunity for adjusting existing requirements and workflows.

The time that takes the facility staff to process the daily work orders was discussed with the facility experts and was compared with the model processing time. This was done by comparing the amount of time taken by the model to prioritize 50 work orders as opposed to the amount of time taken by a facility staff to prioritize the same list. Based on the discussion among the facility experts, they believe that the proposed model can increase the processing speed and hence, positively impact the efficiency and productivity of the staff. However, they highlighted the importance of considering the learning curve of the staff in terms of working with automated systems when first being implemented.

The same list of 50 prioritized work orders by the facility was compared with the prioritization of the same work orders by the developed model. The results of the comparison were discussed with the facility experts to receive their feedback on the accuracy of the model. Based on the feedback received, the participants highlighted that the model is accurate and reasonable in its current version, and it only requires minor adjustments. They believed that analysis and implementation of such models greatly depend on the quality of the data used and therefore, they marked that the accuracy of the developed model can be improved by more comprehensive and consistent data collection by the facility.

In the final step, the facility experts were asked to discuss the advantages and disadvantages of the proposed model, the potential of the model for increasing efficiency, accuracy, and consistency, and provide feedback for enhancing the proposed model. Based on the discussion, the experts believe that because of the nature of the task and depending on the level of information provided when a work order is requested, there is still a need for human intervention. This also highlights the importance of investigating what data should be collected through service requests and in what format to collect comprehensive information and better support the processing and prioritization of work orders. Such approach can reduce the need for human interventions. The facility experts still believed that the proposed model in its current state and automation in general can help with improving consistency, accuracy, efficiency, and productivity of their staff supporting the operation of the facilities. The participants highlighted the significance of defining and developing standards and procedures for different stages of work order processing including receiving work order requests, processing work orders, and data related to the maintenance tasks performed to address the work order to better support data-driven approaches.

5.9 Discussion

This chapter used the work order data of an educational facility to develop a methodology in order to automate the process of prioritizing work orders. Such approach addresses the gap and challenges with user-driven and decision-making methods. Through the process of exploring, cleaning, and preprocessing work order data, insights regarding the current practices and data used by the facility were gained. Performing data exploration and preprocessing allowed the researchers to determine the challenges with the existing approach including data collected, data format, issues with data entry, and information missing. For example, the data cleaning presented the outliers in the database based on the maintenance type. Although the durations determined can be a good indicator of the need for adjustment of the existing practices such as changing maintenance types for some categories or addressing urgent maintenance in less time, the insight gained may also highlight the need for collecting more information such as availability of the staff. In other words, if staff are not available, a work order that has been scheduled may be delayed. Additionally, collecting data regarding the diagnosis process can help with more robust estimation of the duration taken for a work order to be addressed. The data preprocessing also allowed understanding the relationship between different criteria used for processing work orders. This would help with determining the impact of the existing criteria and data in the facility system on the prioritization process while identifying new criteria (e.g., availability of staff, maintenance start date). Identifying information needed for prioritization can help with development of data requirements and guideline while supporting the facilities by allocating resources to collecting data that have impact on their practices. Based on the feedback received from the facility lack of requirements and guidelines have led to inconsistency in terms of data collection and entry. They believed that the proposed methodology could help them with developing their data requirements as well as their guidelines in order to benefit from the data collected (e.g., determine the type of the issues, and how and when to perform follow ups). They also highlighted that the insight would allow them to adjust their existing user-driven practices.

In the next step, the preprocess data was used to investigate the implementation of neural networks for automating the prioritization of future work orders. Two assumptions were made to be able to develop the model. First, due to lack of precise data for start and finished dates and times of the maintenance tasks, the duration between scheduled and completion dates were used for schedule prediction. Second, due to limitations in accessing data of other facilities, the data used for validation process was from the same facility assuming that using new data from the same facility provides different database for validating the model. Out of the information received from the facility, ten criteria were used as input for the neural network model. The duration estimated from date created and date completion was used as the output for the model. Through the development of the model, number of neurons in hidden layer were determined, hyperparameters and their values for model training were defined, and the activation function and the optimizer were selected. Through training set, the weight and importance of each feature in terms of its impact on determining the duration was estimated by the model. Based on the selected loss function, in this case mean squared error, the results of the model training and test presented the optimum network configuration in terms of best parameter values including number of features (criteria) and number of layers. Such method can help facilities to determine the optimum amount of data that needs to be collected assisting with their data requirement development. Additionally, automating the process supports consistency in terms of what criteria is being used for processing work orders. The ML models can be used to benefit from the prior work order prioritization and schedules to prioritize future maintenance work orders. It can also help with defining data requirements and hence increasing consistency while reducing processing time. As discussed in this chapter, neural networks have been used in various fields to prioritize a set of alternatives. With a defined framework, the neural networks can be used to address the maintenance of building facilities by supporting the automation of maintenance work order prioritization. Based on the discussion with a group consisting of three facility experts, the model can increase the efficiency in terms of processing time and accuracy of the existing practices and support the consistency in terms of data collected and criteria used for processing. The facility also highlighted the improved in staff productivity when implementing such methods. However, they highlighted the importance of developing guidelines and requirements to determine how the data should be collected, what data should be collected, and in what format in order to be able to perform analysis based on comprehensive data and receive a more accurate result.

Among the different ML methods, neural network was selected for this study because of five primary reasons. First, neural networks can be used with higher dimensional data corresponding to including more criteria. Such approach allows considering all influential criteria in decision-making leading to more accurate results. Second, neural network allows determining the right number of criteria. Third, neural networks can calculate the weights of the criteria based on the interaction between different criteria and the arrangement of neurons. Fourth, neural network can create the best arrangement itself to make accurate decisions without the need to specify the interaction by the modeler (defining rules in advance) while other ML algorithms require human intervention. fifth, they can be modified and adjusted based on new inputs. If the facility staff make any changes to the rankings and schedules created, the system can automatically learn from the changes occurred and implement that to the future prioritization. Such approach avoids manual changes providing a more practical solution over a longer time span while improving the performance of the system. Implementing data-driven decision-making using neural networks can therefore address human limited cognitive capacity and reduce cognitive workload by performing main part of prioritization task allowing FM staff to focus on abnormalities and emergency situations which require higher decision-making skills. Additionally, processing work orders considering previous input from multiple users allows required adjustments and hence minimization of judgment and cognitive biases' influence.

5.10 Conclusion and Future Research

One of the critical aspects of facility management is the challenge of responding to the high number of work orders submitted daily with limited time and labor available. Existing practices for processing work orders are mainly user-driven and therefore are impacted by staff judgement, experience, knowledge, and biases leading to inconsistency in decision-making. Although decision-making methods (e.g., AHP) have been used to address some of the existing challenges such as inconsistency, they have other challenges including human limited cognitive ability for performing pairwise comparison or limitation of number of criteria used. Late responses or errors in processing can lead to asset failure increasing the cost of operation and maintenance. Data driven methods such as machine learning can benefit from historical data collected, to extract valuable information, find trends, and draw inferences and conclusions supporting and enhancing existing practices.

This chapter reviewed the challenges and gaps with user-driven methods for processing and prioritizing maintenance work orders. It proposed the implementation of machine learning techniques, in this case neural networks, to address the challenges with existing practices for processing work orders including efficiency in terms of performing the time-consuming task of manually processing work orders, accuracy in terms of minimizing errors and providing a practical prioritized list of work orders, and consistency in terms of using the same criteria for processing. The work order data of an educational facility with 213 buildings, and 333,436 work orders collected from 2014 to 2021 was used to explore work order data, gain insight, determine challenges with processing the data, and implement neural networks to automatically prioritize future work orders. The results of the model presented the optimum network configuration. Also based on the discussion with the facility experts, the proposed model and automation in general can assist with enhancing efficiency and accuracy of the existing practices for processing work orders as it allows faster processing with less errors. However, it is significant to determine and develop guidelines and requirements to collect consistent and useful data in order to be able to benefit from data analytics methods. The results of this study can help the facility to determine their best practices and address the challenges with their existing practices to better support the operation of their building facilities.

This chapter contributes to the body of knowledge by developing a methodology to automate the work order prioritization using ANNs. Such approach can enhance the facility maintenance management and support the operation of the building facilities by reducing the processing time, increasing the consistency, and enhancing efficiency resulted from more accurate and updated results over time. Furthermore, this chapter builds the foundation for supporting the operation of smart building. Automation is one of the aspects of smart buildings and this chapter developed a methodology to automate the prioritization of work order.

This chapter had the following limitations. First, the criteria (features) used for the model were limited to the data collected by the educational facility. Future research will consider validating the results of this research by conducting more case studies. Additionally, conducting more case studies will allow validating the impact of other possible criteria on work order processing. Second, due to the data collection process of the work order data, the resercher did not have access to detailed description of the work orders. Future research will explore more detailed work order descriptions (e.g., equipment parts) and include those in the model to provide a more accurate model for processing future work orders. Third, as discussed in the literature, different facilities have different organizational goals. Additionally, facility type may impact the criteria used as well as their ranking. Future research will consider case studies of different facility types to increase the flexibility and applicability of the model to various facilities. Fourth, the output layer used for the study was based on the duration estimated from the existing two dates in the database. Future research will use databases with more accurate data such as prioritization numbering or more accurate dates including maintenance start date to achieve more robust results.

CHAPTER 6: CONCLUSION

6.1 Summary

Facilities management is a multidisciplinary profession constituting more than half of the building lifecycle cost with the majority of it being attributed to operations and maintenance costs. Among many of these FM functions, maintenance-related tasks occupy 79% of the facility managers' responsibilities. Processing and prioritizing work orders constitute an important part of facility maintenance management given the large amount of work orders submitted daily. However, the process taken for prioritizing work orders shows a high dependency on the extent of knowledge and experience of responsible staff available and is challenged by inconsistency in data collection and uncertainty in decision-making. Data-driven methods can provide an advantage over user-driven approaches for processing work orders; however, specific data requirements need to be defined to identify and collect the appropriate data needed and achieve more consistent and accurate results.

In order to determine the challenge areas in existing maintenance practices, a structured literature review was conducted in chapter 2. Three challenge areas of (i) work order processing, (ii) access to relevant information, and (iii) quality control and quality assurance procedures were determined through the literature review. Based on the results, the chapter proposes a conceptual framework connecting the three challenge areas, provides solutions to the challenges and gaps identified, and improves on executing these processes to enhance facility management decision-making. Processing and prioritizing maintenance work orders was selected for further investigation.

A vast amount of work orders is submitted daily, which is a critical component of management for any facility. Making decisions and responding to a high number of requests demand intensive labor hours resulting in delays causing issues for facility managers. Given that, the goal of this research was to automate the process of prioritizing work orders by developing a framework that benefits from neural networks in order to support FM practitioners.

The first objective of this research was to identify the gaps and challenges in existing practices for processing maintenance work orders and to address the following question:

What are the similarities and differences between literature review and existing industry practices in terms of processing and prioritizing work orders?. Chapter 3 provides the results of the literature review in the area of processing work orders as well as unstructured and semi-structured interviews conducted. The chapter determines the data requirements and criteria used by different facilities and identifies gaps and challenges in user-driven approaches. Comparing the results from literature and interviews are then presented to determine the similarities and differences between literature and interviews in terms of existing practices for processing maintenance work orders and identify the best practices. The data collection methods selected for this research allowed determining the gaps in the existing literature and provided the opportunity to expand knowledge in the area of processing work orders. In addition, they assisted with gaining details and in-depth information about the existing user-driven industry practices and their associated gaps and challenges through interviews. While descriptive results such as variability across individuals in terms of criteria selection were provided through this chapter, data from more participants were needed to be able to study the detail of the criteria selection with to their ranking through statistical analysis while investigating the possible impact of other factors such as years of experience. Furthermore, collecting data from a wider range of participants would allow implementing decision-making methods to address some of the challenges identified in the data collected from literature and interviews (e.g., inconsistency).

The second objective was to determine the comprehensive list of criteria used for processing work orders to answer the question of what is the comprehensive list of criteria and their associated rankings for prioritizing maintenance work orders?. The information collected in chapter 3 was used as a basis for developing a survey questionnaire on the criteria selection and ranking among individuals with different years of experience working in different facility types and sizes. Chapter 4 presents the results of the survey questionnaires with 71 participants. The survey results show the overall list of criteria and their ranking for individuals from different facility types and sizes and with different years of experience.

Investigating the possible impact of facility type, facility size, and years of experience on processing and prioritizing work orders was the third objective of this study. The research question for this objective was as follow: Do facility type, facility size, and years of experience impact the list and/or ranking of criteria?. Chapter 4 compares the criteria selection and ranking of participants based on years of experience, facility types, and facility sizes using descriptive and inferential statistical analysis. The results present the possible impact of all three criteria on criteria selection and ranking.

The fourth objective of this research was to identify the common data used in different stages of work order processing and address the following research question: What is the data overlap between the information used for processing work orders and the information collected following the maintenance task?. To do so, Chapter 4 presents the data overlap between different stages of processing work orders and determines that although facilities collect data following the completion of the maintenance tasks, the data collected are not necessarily useful for addressing future work order processing. On the other hand, facilities are not benefiting from the useful data collected following the maintenance tasks to process their work orders.

The criteria and ranking identified through the survey questionnaire conducted in chapter 4 were used to explore the implementation of a decision-making method (AHP) to address some of the challenges associated with user-driven approaches such as inconsistency in criteria selected for work order processing. The chapter provides an example of eight work orders received from an educational facility and walks through different steps of processing and prioritizing work orders using AHP. The chapter concludes by discussing the challenges associated with the implementation of such methods. The results of this chapter combined with chapter 3 can be used for developing data requirements and guidelines supporting the implementation of data-driven decision-making to address the challenges with user-driven approaches as well as decision-making methods. The results of chapters 3 and 4 highlight the challenges and gaps with existing practices. Moreover, they provide the overall list of criteria used for processing work orders as well as criteria and ranking used by different facility types and sizes and among individuals with different years of experience. In order to further address the challenges identified from user-driven and decision-making methods, the chapter proposes the use of data-driven methods such as Machine Learning in order to increase the consistency in terms of criteria used, enhance and support the efficiency of work order processing in terms of processing time, and improve the accuracy of the work order processing by benefiting from work order records.

Finally, the last objective of this study was to automate the prioritization of work orders using neural networks to support processing work orders, increase consistency and accuracy, and enhance staff performance by reducing cognitive workload. This chapter addressed the two following research questions: (i) Can neural network prioritize work orders based on previous schedules created to support accuracy, efficiency, and consistency?, (ii) What is the most efficient neural network structure for prioritizing maintenance work orders?. Chapter 5 presents the implementation of data analytics and data-driven methods, in this case neural networks, to address challenges with the existing user-driven approaches as well as decision-making methods and automate the prioritization of work orders. This chapter uses work order data of an educational facility to benefit from their work order data collected, determine the correlation between different criteria used for processing work orders, learn from the prioritization of their previous work orders, and automatically prioritize future work orders. The criteria requested from the educational facility were selected from the list of criteria identified in chapters 3 and chapter 4. Additionally, the years of experience of staff who processed each work order was requested among the criteria as chapter 4 presented the impact of this factor on criteria selection and ranking. Using criteria from the list determined in chapter 4 would allow validating the importance of the criteria on the prioritization and creation of schedules by investigating their correlation with the schedules. Furthermore, both chapter 3 and chapter 4 presented the selection of a different number of criteria for processing work orders. Implementing a data-driven method would allow determining the optimum number of criteria for work order prioritization. Chapter 3 also marked the difference between criteria ranking within the context of work order prioritization as opposed to ranking outside of the context. Implementing a data-driven approach allows capturing rankings that were used in the actual work order processing situation. Lastly, chapter 3 presented cognitive workload and the impact of coping strategies on work order processing. Automating this process through user-driven approaches would reduce the cognitive workload on human operator supporting their performance. The results of data exploration present the challenges with data collection and entry for the educational facility while also providing insights into the correlation between the selected criteria and work order prioritization as well as facility performance in terms of the duration taken for addressing the work orders. The results of the developed Artificial Neural Network (ANN) model present the most optimum ANN configuration for work order prioritization based on estimated mean squared error. The efficiency of this model in terms of processing time and the accuracy of the model in estimating accurate prioritization were validated through discussion with facility experts recruited from the educational facility. Implementing data-driven methods allow faster prioritization performance leading to less failure and downtimes, reduces the impact of knowledge loss when staff leave the facility, allows focusing on critical thinking and emergency situations, helps with identifying errors and adjusting and updating the system, and assists with identifying important factors and relationship between different criteria supporting the development of data requirements and guidelines.

6.2 Contributions

This research explored the gaps and challenges with existing practices for processing and prioritizing work orders by comparing the results of previous studies with the actual practices through interviews and survey questionnaires. It proposed an automated approach using neural networks to automatically prioritize work orders based on recorded work order data and schedules. The research has filled in the research gap of user-driven and decision-making methods for processing and prioritizing work orders. The research contributions are as follows:

6.2.1 Empirical Scientific Evidence

This research provided the foundation for developing data requirements and guidelines through empirical scientific evidence to better support the processing of work orders. While the interviews conducted through this study added to the insights about the existing practices for processing and prioritizing work orders and their gaps and challenges, in-depth data was collected using survey questionnaires to collect experts' opinions, knowledge, and experiences from a wider range of facility experts and provide empirical scientific evidence in the area of processing and prioritizing work order. Therefore, this research was based on actual data collected rather than developing solutions solely based on assumptions.

The in-depth data collection allowed determining the comprehensive list of criteria used by different facilities, their overall importance, the possible factors influencing the selection and ranking of the criteria, and the common data used in different stages of work order processing. Additionally, the challenges and gaps identified through data collection can be used to improve the existing user-driven practices while assisting with planning for the implementation of data-driven approaches. The in-depth data collection also allowed determining examples of biases and coping strategies in work order processing.

The results can support facilities with developing comprehensive and practical data requirements to collect the required information in the proper format to be able to benefit from the data collected and inform future work order processing. This approach can support data-driven decision-making and enhance the operation of building facilities.

In the final stage of this research, the work order data of an educational facility was used to explore and investigate real work order data, determine the challenges associated with data entry, format, data collection, and storage, and implement machine learning to benefit from work order data collected to automate future work order prioritization. The exploration of real work orders provided examples of poor practices which can help other facilities modify and adjust their existing practices to benefit from their data collection.

6.2.2 Developing a Data-Driven Methodology to Automate the Decision-Making of Facility Maintenance Management

Data Insight. A methodology was developed through this research in order to support an approach for automating the process of prioritizing work orders. Using work order data and data exploration, cleaning, and preprocessing methods, it was possible to determine the correlation between different criteria used for processing work orders and the schedule. Such an approach allowed validating the impact of criteria identified through data collected from interviews and surveys. The correlations determined can also help facility professionals to better identify and develop their data requirements to collect information that has an actual impact on work order processing.

ANN for Prioritization. Through the methodology developed in this research and by implementing ANNs, the prioritization of work orders in an educational facility was automated. This addresses the research gap of user-driven and decision-making methods for processing and prioritizing work orders. The developed methodology can enhance the efficiency, accuracy, and consistency of the existing practices for prioritizing work orders while supporting staff by improving their productivity as the developed methodology reduces their cognitive workload allowing them to focus on emergencies and abnormalities. The methodology developed in this research can be generalized to different facilities and databases as the research is not focused on the specific database but rather on the steps taken in order to benefit from a data-driven decision-making method, in this case neural networks.

Development of Data Requirements. Facilities can implement the developed methodology into their practices in order to identify the useful information (criteria) collected in their facility, adjust their data collection to capture other useful data, use as many criteria as needed, and determine the optimum amount of information and criteria needed in order to automate the prioritization of their work orders. This approach supports facilities with spending their resources on the collection of valuable data while providing support for better maintenance management planning. Additionally, the development of data requirements and guidelines provides high-quality data to support other maintenance practices.

Foundation for Smart Buildings. This research provides the foundation for supporting smart building by contributing to the automation of one of the FM practices. One main feature of smart buildings is automation, and this research explored the automation of work order prioritization based on historical work order data benefiting from data-driven decision-making. Existing user-driven practices for processing work orders are prone to errors as they are impacted by staff knowledge, experiences, biases, and coping strategies. Additionally, automating the prioritization of the work orders greatly reduces the time taken for processing work orders enhancing the performance and operation of the building facilities. Furthermore, there is a great difference between the time taken by an FM staff to process the work orders compared to an automated system. Automating such processes can enhance the operation and maintenance of building facilities and improve their efficiency.

6.3 Limitations

This research had the following limitations, which will be addressed in future research efforts.

6.3.1 Data Collection

The interviews conducted covered 17 participants from five different facility types. Additionally, the survey participants were unevenly distributed and mostly came from commercial, educational, mixed-use, and government facilities. Having different subsample sizes as well as small subsample sizes impact the results of statistical analysis and therefore, this research only addressed inferential statistical analysis.

6.3.2 Work Order Data

As discussed in previous chapters, the data collected by facilities have many challenges such as lack of comprehensive data collection for informing prioritization of future work orders. As the implementation of the neural networks required access to actual data, the work orders received from an educational facility were used. However, based on the results of data exploration and correlations determined, not all the criteria and information collected by them were beneficial for work order processing. Additionally, the entry date (the date the work order was assigned) was used for the model developed in this research. However, this date can differ from the date when the shops/maintenance staff start addressing the work orders. Future research should identify a facility that collected more detailed data regarding the dates and times the work orders were requested and scheduled as well as the date the maintenance tasks started and were completed.

6.4 Future Research

Based on the work conducted in this research as well as its limitations of it, the following areas are proposed for future research.

6.4.1 Data Collection

Future research will address collecting data from all types of facilities with almost the same number of individuals from each facility to be able to perform a more robust comparison and investigate correlation through statistical analysis.

6.4.2 Work Order Data

Future research will explore more case studies in order to investigate other criteria not included in this research, adjust the developed model accordingly, and further validate the results of this research.

6.4.3 Developing a System Connecting Different Stages of Work Order Processing

While this research was focused on processing and prioritizing work orders, future research will consider the connection between different stages of work order processing to develop a comprehensive model and system supporting all the stages of work order processing through automation.

6.4.4 Integration with Other Systems & Advanced Technologies

The developed methodology through this research can be integrated with other FM systems (e.g., CMMS, CAFM) as well as BIM, Power BI, and advanced technologies. The FM systems and BIM are used as data repositories storing the information related to assets that are managed by the facilities, while at the same time, they can provide access to visual information such as the location of the assets to further support the FM staff. Future research will investigate the integration of these systems with the developed methodology in order to use the data stored in such systems to prioritize maintenance work orders. Furthermore, advanced technologies such as sensors can be investigated to further automate this process by automatically collecting data following the completion of the maintenance tasks such as information related to time spent on the task and the number of crews who performed the task.

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APPENDIX

Appendix A: Survey Questionnaire

Hello,

I am Mahnaz Ensafi, a Ph.D. student in the Department of Building Construction at Virginia Tech. I would like to ask you to participate in my research study addressing the process of prioritizing work orders and creating schedules. The goal of this survey is to understand what criteria are used by facility experts to process and prioritize work orders and what is the level of significance for each criterion. The objective of this research is to develop a workflow to assist facility experts in processing work orders. The developed workflow can provide consistency in the decision-making process as well as proposing a solution to support the operation and management of any facility.

Your Participation

This survey includes 10 questions, and it will take approximately 10 to 15 minutes to be completed. Your participation is voluntary. If you decide to participate in this study, you may withdraw from your participation at any time without penalty.

Risks and Discomforts

There are no known risks associated with this research. This survey does not collect any personally identifiable information.

Protection of Confidentiality

No identifying information on the participants will be collected. The data will be collected anonymously and reported in the aggregate only, with no individual responses included in the published reports.

Please consider responding to the last question if you would like to receive a summary of the survey or if you are willing to provide further information through a personal interview.

This research has been reviewed by the Virginia Tech IRB under protocol IRB- 20-879. Please do not hesitate to contact the researcher if you have any questions or concerns.

E-mail address: mensafi@vt.edu

Consent Question

Do you agree to voluntarily participate in this survey?

o Yes

o No

1- What is your level of involvement with processing work orders?

- ○ Directly involved
- ○ Indirectly involved
- ○ Not involved

2- How many years of your facility management experience has a focus on maintenance work order processing?

- ○ Less than 1 year
- ○ 1-5 years
- ○ 5-10 years
- ○ 10-20 years
- ○ Over 20 years
- ○ I don't have experience, but I am familiar with the process

3- Based on online documentations and initial interviews, the following is a list of criteria considered for prioritizing work orders. Please drag and drop the criteria that you use into the box and move them up and down to rank them (the higher the criterion is placed, the more important it is).

Items	Drag, Drop, & Rank the Criteria
□ Zones (if the facility is divided into different zones) □ Type of building (e.g., offices vs. laboratories) □ Building Age	

□ Distance between the service center and the building under the work order □ Type of space □ Availability of maintenance staff to perform the maintenance □ Availability of resources (e.g., material, equipment) □ Energy usage □ Indoor environmental quality □ Maintenance cost □ Budget □ Maintenance duration □ Level of severity (hazards) □ Failure frequency □ Severity of failure □ Remaining life cycle □ Level of risk □ Association between different equipment/system (e.g., if the equipment is connected to another equipment impacting it if shut down is required) □ Maintenance difficulty □ End date □ Occupants' preferences\satisfaction □ Codes and regulations □ Others, please specify _______ □ Others, please specify _______ □ Others, please specify _______	

4- Where is your organization located? (Please specify the country)

5- What is the type of the organization you are currently working at?

- Educational Institution
- Healthcare
- Commercial
- Residential
- Industrial
- Mixed-Used, please specify
- Others, please specify

6- What is the range of building sizes in your organization (sq ft)?

- Size is the same (please specify the size)
- Size varies (please specify the range)

7- What is the number of buildings in your organization?

- 1-5
- 6-10
- 11-50
- More than 50

8- Do you manage the work orders for all the buildings in your organization?

- Yes
- No (Please specify how many buildings you manage)

9- Please list the key information you need to be able to make an efficient decision to process the work orders submitted (e.g., room number, work type, location of the work order such as wall or ceiling, distance from the service center).

10- Following the completion of each maintenance task, what information is collected/recorded? (Check all that applies)

- ☐ No further information is collected
- ☐ Duration of task (start and end date)
- ☐ Total hours spent on the task
- ☐ Number of crew members
- ☐ Issue description (prepared by the technician)
- ☐ Number of visits to complete the task
- ☐ Percentage completion of the tasks in each visit
- ☐ Quantity of spare parts required
- ☐ Material/resources cost
- ☐ Difficulty with repair
- ☐ Others (please specify)

(Optional) If you would like to receive a summary of the survey or if you are willing to provide further information through a personal interview, please check the related box and provide your contact information (name & last name, email/phone number).

- ☐ Receive Summary

- ☐ Personal Interview

Appendix B: ADAM Optimizer

$$w_{t+1} = w_t - \alpha m_t$$

$$m_t = \beta m_{t-1} + (1 - \beta)\left[\frac{\delta L}{\delta w_t}\right] \tag{1}$$

m_t= aggregate of gradients at time t (current)

m_{t-1}= aggregate of gradients at time t-1 (previous)

w_t= weights at time t

w_{t+1}= weights at time t+1

α_t= learning rate at time t

δL= derivative of loss function

δw_t= derivative of weights at time t

β= moving average parameter

$$w_{t+1} = w_t - \frac{\alpha_t}{(v_t + \varepsilon)^{\frac{1}{2}}} * \left[\frac{\delta L}{\delta w_t}\right]$$

$$v_t = \beta v_{t-1} + (1 - \beta) * \left[\frac{\delta L}{\delta w_t}\right]^2$$

(1)

w_t= weights at time t

w_{t+1}= weights at time t+1

α_t= learning rate at time t

δL= derivative of loss function

δw_t= derivative of weights at time t

v_t= sum of square of past gradients

β= moving average parameter

ε= a small positive constant (10^{-8})

$$\widehat{m_t} = \frac{m_t}{1- \beta_1^t}$$

$$\widehat{v_t} = \frac{v_t}{1- \beta_2^t}$$

$$w_{t+1} = w_t - \widehat{m_t}\left(\frac{\alpha}{\sqrt{\widehat{v_t}} + \varepsilon}\right) \tag{2}$$

Appendix C: Code Examples

This section provides code examples for preprocessing and model development stages.

1) Normalizing the data

```
scaler = MinMaxScaler(feature_range=[0, 1])
X_fit_rescaled = scaler.fit_transform(X_fit)
Y_fit_rescaled = scaler.fit_transform(Y_fit.reshape(-1, 1))
```

2) Creating the model layers

```
for i in range(1, n_layers):
    if i==1:
        # First layer
        model.add(Dense(first_layer_nodes, input_dim=X_fit.shape[1],
                    kernel_initializer = init_mode, activation= "relu"))
    else:
        # Hidden layers
        model.add(Dense(n_nodes[i-1],    kernel_initializer    =    init_mode,
activation="relu"))

#Output layer
model.add(Dense(1, kernel_initializer = init_mode, activation = 'sigmoid'))
```

3) GridSearch

```
grid_search = GridSearchCV(estimator = estimator, param_grid = parameters,
                    scoring = ['neg_mean_squared_error'],
                    cv = 2,
                    n_jobs = 1,
                    refit = 'neg_mean_squared_error',
                    verbose = 22)
```