The Impact of Sales Forecasting Management on Business Performance

A Case Study at Palo Alto Networks

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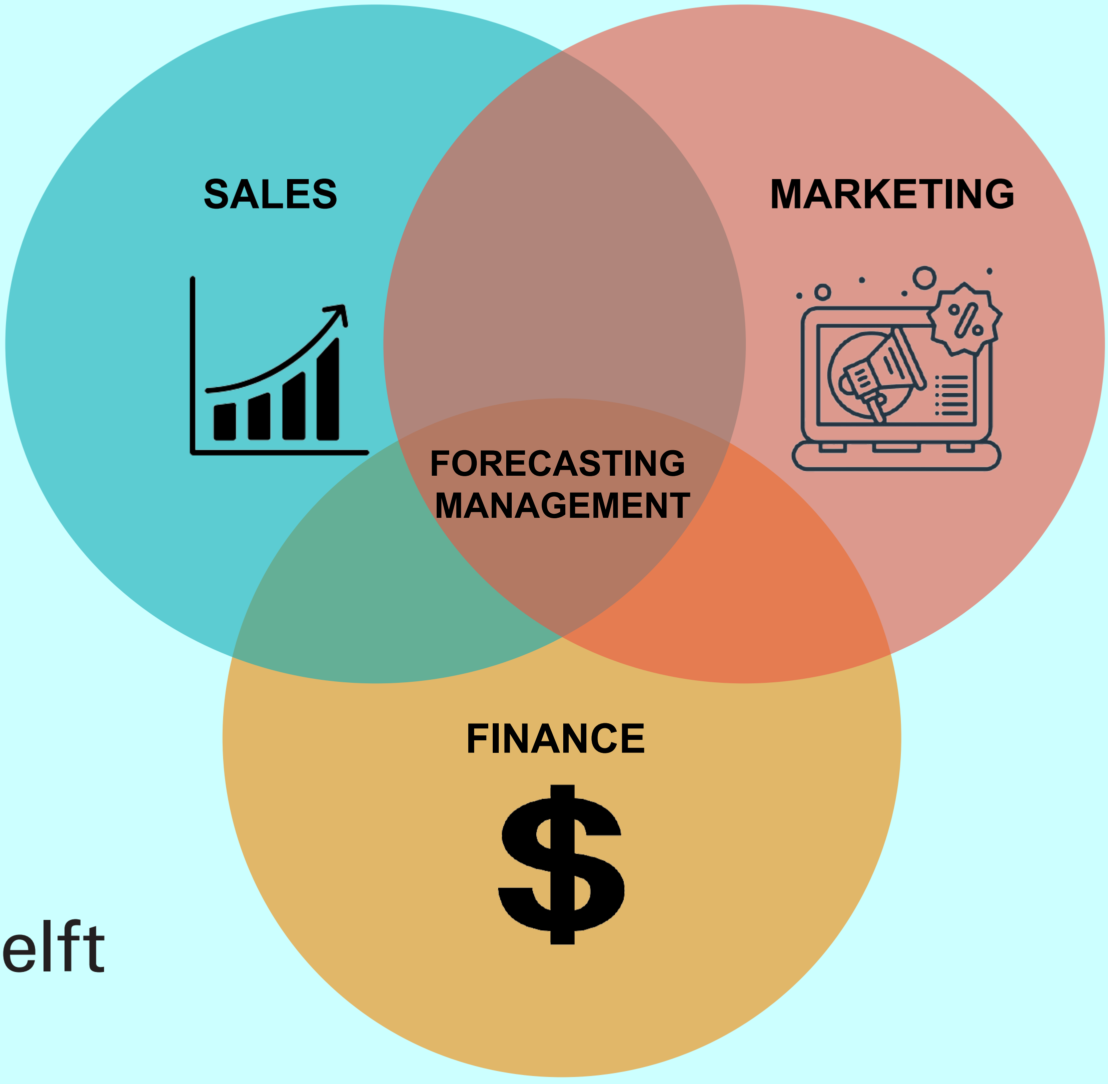

TU Delft

The Impact of Sales Forecasting Management on Business Performance

A Case Study at Palo Alto Networks

by

Uthra Moorthy

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Summary

The aim of this study is to improve the sales forecasting performance in a high-tech industry and to study the impact of forecasting on the organization's business performance. The thesis is applied research at a leading high-tech cyber-security company, Palo Alto Networks. As part of the internship at Palo Alto Networks for the Sales Finance team of Europe, Middle East, and Africa (EMEA), it was evident that there is a need to improve the sales forecasting performance. One of the important responsibilities of the Sales Finance team is to predict the operational expenditures of the company as close as possible to the actual expenditure since it has a huge impact on the stock price and the investment decisions. The End of Service Benefits (EOSB) is the gratuity payment received by the employees of the company when they are terminated or resigning from the job. It is a crucial operational expenditure which is proportional to the salaries earned by the sales employees. In the thesis, the EOSB of the sales employees is the performance outcome measured. The salaries of the sales employees are dependent on the sales or bookings and the sales compensation structure of the company. The EOSB is also dependent on labor laws. Thus, along with sales forecasts, the compensation structure and the labor laws are also considered to predict the final business outcome. And to define the scope of the thesis, the sales and the EOSB are predicted for sales employees in the United Arab Emirates (UAE) region. The sales forecasting model should consider different organizational components to make accurate sales and EOSB predictions. This shows that organizational characteristics play an important role in sales forecasting performance. From an academic perspective, there is extensive research on forecasting methods but the effect of organizational characteristics on sales forecasting is not clearly studied. Moreover, the effect of sales forecasting on a business outcome is not measured quantitatively. Hence the following problem statement was formulated,

There is not a clear understanding of how the organizational characteristics can affect the forecasting practices within the organization. Additionally, there is also a mismatch in the literature regarding the appropriate forecasting method that can be used to predict sales. Finally, the organizations are not aware of the effect of sales forecasting performance in predicting an important operational expenditure, End of Service Benefits and it is also not available in the literature.

Based on the above problem statement, the following research question is formulated,

How can a high-tech organization (Palo Alto Networks) improve its business performance using sales forecasts?

Based on the research objective and literature review, a sales forecasting management framework was chosen and reconstructed. The framework includes sales compensation structure and other organizational factors that have an impact on both sales and EOSB forecasts. The study shows that leadership support, the Product Life Cycle (PLC) stage of the company, Information Logistics, and Cross-Functional communication are some of the organizational factors which have an effect on the sales forecasting performance. These factors of the sales forecasting management framework are also coherent with Palo Alto Networks. Hence these factors were chosen and the modified framework provides the basis for the research.

The next part of the thesis utilizes different forecasting methods available in the literature to build a sales forecasting model under the empirical context of Palo Alto Networks. An appropriate sales forecasting method is chosen based on the variance between the revenue generated from the predicted sales versus the revenue generated from actual sales. The results of the study show that a combined qualitative and quantitative forecasting method is the most appropriate method to predict sales. The inputs of the forecasting model are the qualitative estimates provided by the sales employees in the Salesforce application. Regression analysis is performed to choose the inputs of the model and to find the correlation of each input on the sales. Finally, the sales forecasting model is combined with sales compensation structure and the UAE Labor Law to predict the End of Service Benefits of UAE-based sales employees. The results show that the EOSB predicted using the sales forecasting model has a very low variance of around -2%. This shows the high applicability of the developed model by the organization and thus increases the managerial relevance of the thesis.

The software applications that were used extensively to build the forecasting model include Salesforce, Google Cloud Platform, Tableau, and Excel. This proves the importance of a well-integrated information system within the organization to boost efficient data transfer. The cross-functional communication between different teams such as sales planning, sales operations, sales finance, and business analysts was indispensable to build the forecasting model as it aids knowledge transfer among different teams. These insights validate the components of the modified sales forecasting framework under the organizational setting of Palo Alto Networks and thus increases the academic relevance of the thesis.

Based on the results, the modified sales forecasting framework is validated and it proves the importance of the different organizational factors to improve the sales forecasting performance. Also, for the organization that has the product life cycle stage in the growth or maturity stage with dynamic sales, it is recommended to use the quantitative forecasting method built based on the sales department's estimates. The thesis also finds that the SFM framework has to be adjusted to include the sales pipeline stages as an important organizational factor that influences sales forecasting management. Thus, the thesis provides an interesting insight to include the sales pipeline stages in the framework to improve the sales forecasting credibility.

Acknowledgements

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Uthra Moorthy

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1
Introduction

1.1. Introduction

Sales forecasting plays an important role in organizational decision-making and improving the sales forecasting performance has been an intention for managers. This has increased the focus on sales forecasting management literature in the past decades (Davis and Mentzer, 2007). In the current situation with high demand and competition prevalent in the high-tech industry, connected planning is required to facilitate faster and accurate forecasts that enable agile decision-making (Zorn and Reichel, 2020). The paper (Šečkute and Pabedinskaite, 2003) conducts a survey among U.S production managers which confirms that around 70% of them use sales forecasts as the principal forecasting data. The sales of the company are also used to calculate the relative market share forecasting which is important data for strategic planning (Šečkute and Pabedinskaite, 2003).

Companies need to realize that sales forecasting is a critical management function and plays a vital role in an organization's success (Moon et al., 1998). In the paper (Moon et al., 1998), the authors confirm the existence of a relationship between sales forecasts and the organization's compensation structure. In addition to that, the authors clarify that cross-functional communication between different departments like marketing, finance, sales are important to improve the accuracy and reliability of the sales forecasts. There is ample evidence in the literature explaining the role of sales forecasts in an organization's strategic decision-making and formulating financial business plans. One of the key strategic plans is designing the compensation structure for sales employees. In addition to that, sales forecasting plays an important role in predicting the operational expenses of the organization, thereby affecting the operating margin, profit, net income, and stock price of the organization. To meet the shareholders' interests, it is indispensable to critically review and analyze its financial perspective where forecasting becomes crucial. On an organizational level, forecasting has a direct impact on the financial health of the company (Moon et al., 1998). Hence the thesis has an alternate approach, where the sales forecasting framework available in the literature is quantified and tested under the empirical setting of a high-tech industry such as Palo Alto Networks. It conceptualizes the sales forecasting practices mentioned in the framework into a simulation model to predict a crucial operational expenditure for the company – employee earnings. Employee earnings is an important operating expense and a business outcome for a company and from a higher level, an increase in earnings volatility reduces the quality in matching expenses to revenues (Dichev and Tang, 2009). This increases the need for accurate forecasting methods to improve the forecasting performance and earnings predictability thereby reducing the volatility of earnings.

As part of the thesis, a case study is carried out at a leading cybersecurity company, Palo Alto Networks. Palo Alto Networks is a Fortune 500 company that offers cybersecurity solutions including advanced firewalls and cloud-based offerings. The Europe, Middle-East, and Africa (EMEA) division of the company is growing at a fast pace urging the company to make wise decisions regarding investments. Sales are the backbone of the company, and it is essential to increase the accuracy of the forecasts. In this case, this forecast would be used by the financial department to predict the operational expenses for the company by predicting the End of Service Benefits (EOSB). EOSB is the payment made to the employee upon termination/resignation.

Finally, being listed as a public company, the accuracy in forecasting will help the management to improve the financial health of the organization, make quality decisions that align with the goals and strategies of the company, improve the image of the company among investors. Considering the cost that a company should pay as the result of poor sales forecasting performance, there is no doubt that forecasting is important.

The thesis aims to conceptualize the Sales Forecasting Framework by studying the characteristics of the high-tech industry to build a model that improves sales forecasting performance and study the effects of sales forecasting performance in predicting a business outcome on a granular level (end of service benefits).

1.2. Research Objective

Due to turbulent and dynamic markets prevalent in the cyber-security industry, it is crucial to adopt sales forecasting practices as a management function. Firstly, it is important for the organization to understand the impact of sales forecasting on business practices/outcomes. In the article (Davis and Mentzer, 2007), the authors mention that the results of the surveys indicate that qualitative methods such as executive opinions are used more than quantitative methods. There is extensive research on the forecasting methods used, which indicates that quantitative methods provide better results than qualitative methods. This refers to a mismatch between the literature and practice. Moreover, there is an increased need for collaboration between marketing, sales, and finance teams to create accurate forecasting models. The article (Fildes and Hastings, 1994) discusses a forecasting system where cross-functional teams such as marketing, sales, and finance are involved in the sales forecasting management process. This shows that the business practices within the organization, its structure, the product type, the marketing objectives, information flow processes, the sales department performance are all interlinked when it comes to forecasting management. The statistical characteristics, accuracy, and uncertainty of the forecast are highly affected by organizational practices (Fildes and Hastings, 1994). Hence in this study, the organizational characteristics are studied to develop a forecasting model. Finally, there is also an increased need to find the impact of sales forecasting on business outcomes. The article (Davis and Mentzer, 2007) mentions that by developing the sales forecasting capabilities, an organization is associated with improved profitability, better customer service, and improved financial health. Hence it is important to quantify and evaluate the impact of sales forecasting performance on the business outcome. In this thesis, the business outcome that is measured is one of the important operational expenditures of the company, End of Service Benefits which is related to employees' salaries. From the above statements, the problem statement is defined as follows:

There is *not a clear understanding* of how the organizational characteristics can affect the forecasting practices within the organization. Additionally, there is also *a mismatch* in the literature regarding the appropriate forecasting method that can be used to predict sales. Finally, the organizations *are not aware* of the effect of sales forecasting performance in predicting an important operational expenditure, End of Service Benefits and it is also not available in the literature.

Based on the above, the objective of this study is stated below:

- To propose a modified Sales Forecasting Management framework based on the characteristics and context of the organization.
- To investigate ways to quantify the modified Sales Forecasting Management framework that capture the characteristics of the organization.
- To extend the model to predict the business outcome (end of service benefits) and study the effects of sales forecasting performance on the business outcome.

1.3. Research Questions

Section 1.2 explained the research problem and the research objective that will be addressed in this thesis. Based on the above-mentioned acknowledgments, the main research question of the thesis is stated below:

How can a high-tech organization (Palo Alto Networks) improve its business performance using sales forecasts?

The proposed study presents a theoretical and empirical contribution to improve the business performance of the high-tech industry. The main research question is evaluative, as it proposes research that assesses the role of sales forecasts in improving business outcomes. From the main research question, the following three sub-questions are generated:

1. What are the characteristics of a high-tech company (Palo Alto Networks) that influence sales forecasting management? *(Literature Study & Case Study)*

2. What is the appropriate forecasting technique that predicts sales for the given high-tech industry (Palo Alto Networks)? *(Case Study - Qualitative and Quantitative Data Analysis)*

3. What is the effect of sales forecasts on the business performance (end of service benefits)? *(Case Study - Quantitative Data Analysis)*

The answer to the **first sub-question** gives an overview of the current setting and characteristics of the organization based on the case study at Palo Alto Networks. Based on the results of the first sub-question, suitable forecasting methods are identified and shortlisted. These methods are evaluated and the quantified sales forecasting model is built using the Excel software which gives the results for the **second sub-question**. Finally, the **third sub-question** will help to quantify the effect of sales forecasting performance on the business outcome (end of service benefits) such that the organization can improve the accuracy of predicting an important operational expenditure of the company.

1.4. Relevance of the Study

As mentioned previously in section 1.2, an ample amount of literature is available regarding sales forecasting methods and models. And the literature also has a theoretical framework that conceptualizes the organizational factors with sales forecasting management procedures. But in the article (Moon et al., 2003), the authors mention the need to quantify the impact of sales forecasting practices that goes beyond performance measures like accuracy/sales. Further, there is a necessity to validate the available sales forecasting framework in the literature in a broader range of organizations and industries (Davis and Mentzer, 2007). By answering the research question, the thesis aims to modify and validate a sales forecasting framework available in the literature. The framework is chosen such that the effect of the organizational factors is connected with the sales forecasting practices. In this study, the framework is quantified using the data of Palo Alto Networks. Finally, finding the effect of sales forecasting on End of Service Benefits will also contribute to utilizing the available framework in the literature to generate a novel business insight. Thus, the thesis aims to contribute by fulfilling the above-mentioned knowledge gap in the literature.

From a managerial perspective, the problem is relevant since this is a current problem faced by the organization and the manager believes that it needs to be improved in the department. Specifically, the End of Service Benefits is one of the important operational expenses for the company and is an important component to take into consideration when proposing a business plan related to investments at the beginning of the fiscal year. The End of Service Benefits is driven by employees' earnings that include their base pay and commissions. The commissions of salespeople are highly dependent on the sales they incur. Hence the prediction of sales forecasts becomes highly relevant to determine the earnings of sales employees. This provides practical relevance to improving sales forecasting performance in the organization and reduces the impact of forecast inaccuracies on the Earnings per Share (EPS) and stock value.

1.5. Thesis Outline

The thesis is divided into 7 chapters and the outline is provided below. The table below gives an outline of the thesis with respect to sub-questions.

1. **Chapter 1** gave a detailed introduction of the research, the motivation of the thesis, followed by the problem statement; based on which the research objectives and research questions are formulated. The chapter concludes with the relevance of the research and the thesis outline.

2. **Chapter 2** will provide the research methods to answer each sub-question and finally to answer the main research question.

3. **Chapter 3** consists of the literature review that covers the relevant topics that are required to perform the research. This includes the literature regarding sales forecasting management, the framework that connects the sales forecasting practices with organizational factors, the organizational characteristics that should be studied to choose forecasting methods, followed by the available forecasting methods in the literature.

4. **Chapter 4** covers the current organizational setting of Palo Alto Networks as this thesis is a case study performed at that company. The company's organizational characteristics are studied and interpreted based on the literature study. Finally, the sales forecasting framework is modified based on the organizational setting and the characteristics from the modified framework are explained.

5. **Chapter 5** discusses the data collection, data analysis part of the thesis. Based on the results of chapter 4 and the literature study, data is collected and analyzed. Further, different forecasting methods as discussed in the literature study are evaluated and an appropriate sales forecasting method is chosen.

6. **Chapter 6** uses the chosen sales forecasting method to predict the business outcome. The forecasting method built as a result of Chapter 5 is extended to predict the sales commissions of the employees, followed by the salary predictions. Finally, this commission model is used to predict the end of service benefits and compared with the current forecasting method used in the organization. By quantitatively developing a forecasting model based on the modified sales forecasting framework, the effect of sales forecasting performance on the business outcome is studied.

7. **Chapter 7** will discuss the results of the thesis by answering the sub-research questions and thereby answering the main research question. It also provides limitations, directions for future research, and self-reflection.

Chapters	Outline	Objective
Chapter 2	Research Methods	This chapter aims to explain the selection criteria for relevant literature review and the research steps carried out in the thesis study to answer the main research question. It provides the basis for all the chapters below.
Chapter 3	Literature Review	The main objective is to choose a theoretical sales forecasting framework and the available forecasting methods in the literature that helps the organization to improve sales forecasting performance and thereby the business performance.
Chapter 4	Sub-question 1 - *What are the characteristics of a high-tech company (Palo Alto Networks) that influence sales forecast-ing management?*	This chapter aims to provide the context of the organization - Palo Alto Networks and modify the theoretical framework suitable for the research scope.
Chapter 5	Sub-question 2 - *What is the appropriate forecasting technique that predicts sales for the given high-tech industry (PaloAlto Networks)?*	The forecasting methods shortlisted as a result of literature study are validated and an appropriate sales forecasting method is chosen in this chapter.
Chapter 6	Sub-question 3 - *What is the effect of sales forecasts on the business performance (end of service benefits)?*	This chapter combines the sales forecasting model with the sales compensation structure of the company and the UAE Labor Law to predict the final performance outcome - End of Service Benefits
Chapter 7	Results	The aim of this chapter to summarize the results of the study along with generalizability, novelty and future directions of the research.

Table 1.1: Thesis Outline corresponding to research questions

2

Research Methodology

This chapter provides an overview of the research steps carried out to answer the main research question. It begins with the explanation of the literature review followed by the research design which includes the study of organizational setting, data collection, and data analysis methods to answer the main research question.

2.1. Selection of the Literature

The literature review started with a broader search of the keyword "Sales Forecasting Management" in the google scholar database. This is done in order to understand the importance of sales forecasting management in an organization. After the initial search, the articles (Mccarthy et al., 2006), (Mentzer and Moon, 2004) were chosen to understand the needs and importance of sales forecasting management within an organization. The results of this search are tabulated in the literature review chapter in the figure 3.1. As mentioned in the chapter 1, the main aim of the thesis is to improve the business performance of an organization using sales forecasting. Hence the keyword "organization" was added with the search. It leads to the article (Davis and Mentzer, 2007) titled "Organizational factors in sales forecasting management". The abstract of the article shows that the authors have developed a theoretical sales forecasting management framework to improve business performance. Furthermore, the framework includes the impact of organizational factors in forecasting performance. This framework (3.1) is chosen as it aligns with the research objective of the thesis and the article is published in the journal, "International Journal of Forecasting" which has a good impact factor (>3) and a citescore.

The second part of the research was carried out to determine the existing sales forecasting methods, and there are many articles and books written in the last few decades on this topic. The literature for forecasting methods is vast and hence limiters were used in Scopus related to the subject area in business along with the keywords 'Sales Forecasting' and it led to 56 results. Following this search, the article's title, abstract, and subsections were checked to understand the types of forecasting methods applied by the authors under different business settings. A search was done using the same keywords such as 'sales forecasting methods' in other databases such as Google Scholar, Elsevier, etc which lead to the same articles repeatedly. These articles provided an overview of the types of forecasting methods – Qualitative and Quantitative methods.

Hence the search was redefined using the keywords 'Qualitative and Quantitative Sales Forecasting' methods in the TU Delft repository & Google scholar and the recurring articles were chosen. The articles provided more insights into the relationship between the product life cycle to the type of forecasting technique. This is coherent with the course materials of MOT1533 – High Tech Marketing and to position and assesses the company's product stage, the book (Kotler, 2016) is used to explain the product life cycle characteristics. Further, including the keywords 'product life cycle', 'forecasting methods' and 'forecasting management', the articles with the best match and highest number of citations explain how the product's life cycle was used as a prime determinant of the forecasting method.

Some of the articles that were chosen after a thorough revision of the abstracts are (Šečkute and Pabedinskaite, 2003), (Mccarthy et al., 2006), (Doyle and Fenwick, 1976), (Mishra and Prasad, 2004) and (Chambers et al., 1971). These articles provide an overview of the qualitative and quantitative methods in sales forecasting along with the advantages and disadvantages of each method. The results of this search have been tabulated in the figure 3.4.

For the literature review, various databases like 'Google Scholar', 'Scopus' and TU Delft repository were used. The databases produced various results and hence an inclusion criterion was added in the search to limit it to books, papers, and articles. Some of the basic selection criteria include the filtering of documents that are available in English and full text online. For the extended selection criteria, the citing score or impact factor of the journals in which the articles have been published were checked using Scopus. Further, the title and abstract of the article were skimmed to check if the article matches the search description.

2.2. Research steps

This section provides the visualization of the step-by-step procedure carried out to answer the main research question. The main research activities that were carried out in the thesis study include literature review, organizational setting, data collection, data analysis, and final measurement of performance outcomes. Each part of the research steps helps in answering a sub-question as mentioned in the 1.3.

The figure below 2.1 explains the flow diagram of research steps. The research activities that are included are explained as follows:

- Organizational Setting
  The main aim of the thesis is to improve the sales forecasting practices in an organization and study their impact on business performance. It is important to choose a framework that considers sales forecasting as a managerial function and links the managerial and organizational practices with the sales forecasting performance. Hence the research steps started with the literature review that chooses a sales forecasting framework design as mentioned in the section 3.1.1. Secondly, the framework is modified to suit the particular organization under study - Palo Alto Networks and the specific business outcome. As mentioned in the section 1.2, the business outcome that is measured and studied in this thesis is the End of Service Benefits. The components of the framework are chosen and modified based on the specific research objective and the organization itself. Table 4.5 provides the justification for each component used in the modified SFM framework along with the comparison of the original SFM framework. The results of this step are twofold - choose a framework that provides the basis for the thesis and studies the sales forecasting climate of the organization. Finally, it answers the first research sub-question of the thesis.

- Data Collection
  This research step explains how the data is collected, retrieved, and filtered based on the research scope. As mentioned in the section 1.1, the scope of the research is specific to predict sales made by the employees of the region United Arab Emirates (UAE). This is because of the high operational expenditure related to End of Service Benefits of this region and the complexity involved in predicting it since it is influenced by the external factor, namely the UAE Labor Law. The data is filtered using data management software (Tableau) to match the research scope and the filters used are mentioned in the section 5.1. The research design as mentioned in the figure 5.1 provides the basis for data collection.

- Data Analysis
  This step is important since it improves the efficiency of the sales forecasting performance by using the most appropriate forecasting method to predict sales. It includes the organizational characteristics as given in the modified sales forecasting framework (SFM) framework (Fig: 4.1) and plays a crucial part in validating the framework and answering the second sub-research question. The research method followed in choosing the appropriate forecasting technique is mentioned in the figure 2.2. The detailed explanation of each method and the results are discussed in the chapter 5.

- Performance Outcomes
  This part of the research steps explains the final component of the sales forecasting management (SFM) framework. The chosen sales forecasting model is extended to predict the employee salaries and commissions based on the sales compensation structure of the organization. Followed by that, the results of the predicted employee commission are compared against the current organizational practice to predict End of Service Benefits - assuming the employee will achieve the target and receive the On-Target

Incentive as the commission. As mentioned in the problem statement 1.2, the current problem faced by the organization (Palo Alto Networks) is in predicting the End of Service Benefits for UAE employees as it is an important operational expenditure of the company. Due to this, there is a huge need to improve the sales forecasts and thereby the End of Service Benefits forecasts. Based on the results of this step, the final model is built to predict the End of Service Benefits. The performance outcome provides a quantified validation if the modified sales forecasting framework can be used for improving the sales forecasting performance and thereby the business performance. Finally, this research step provides the answer for the third sub-question.

The performance measurement that is used to validate the forecasting model at the data analysis and the performance outcome steps is the **average variance** of the predicted values with respect to the actual values. In the case of the sales forecasts, the variance represents the difference between the total contract value/revenue made by the actual sales bookings vs the predicted sales bookings. In the performance outcome stage, the average variance is calculated as the difference between the predicted commissions vs the On-Target Incentive (OTI) earned by the sales employees. The final performance outcome measured is the End of Service Benefits (EOSB) and the average variance in figure 6.3 is the EOSB calculated using the predicted commissions vs the EOSB calculated using the On-Target Incentive (OTI). The variance is chosen as the performance measurement since it determines how accurate are the forecasts. The top-level management and the investors are interested to have less variance between forecasts and the actual expenditure as it has an impact on the stock price and investment decisions.

The data that is flowing from the Salesforce to Google Cloud Platform serves as the source for the analysis that is carried out in the later chapters of the thesis.

Finally, this chapter provides the flow of the thesis as each research step mentioned above is defined as separate chapters in this study. The sub-questions are answered based on the case study at Palo Alto Networks and the results are applicable for a high-tech company with a similar organizational setting and characteristics. The realization degree and the generalizability of the sales forecasting model will be explained in the final chapter 7.

This research is based on two types of research namely descriptive and explorative. The descriptive nature of the research comes from the steps carried out in the literature review to answer the first sub-question - Organizational setting. The development of the sales forecast model is explorative in nature since the parameters that have a significant relationship with sales are chosen based on regression analysis. This means that the research methods carried out in this study are scientific and it provides an exploration of both theory and practice as mentioned in chapter 5.

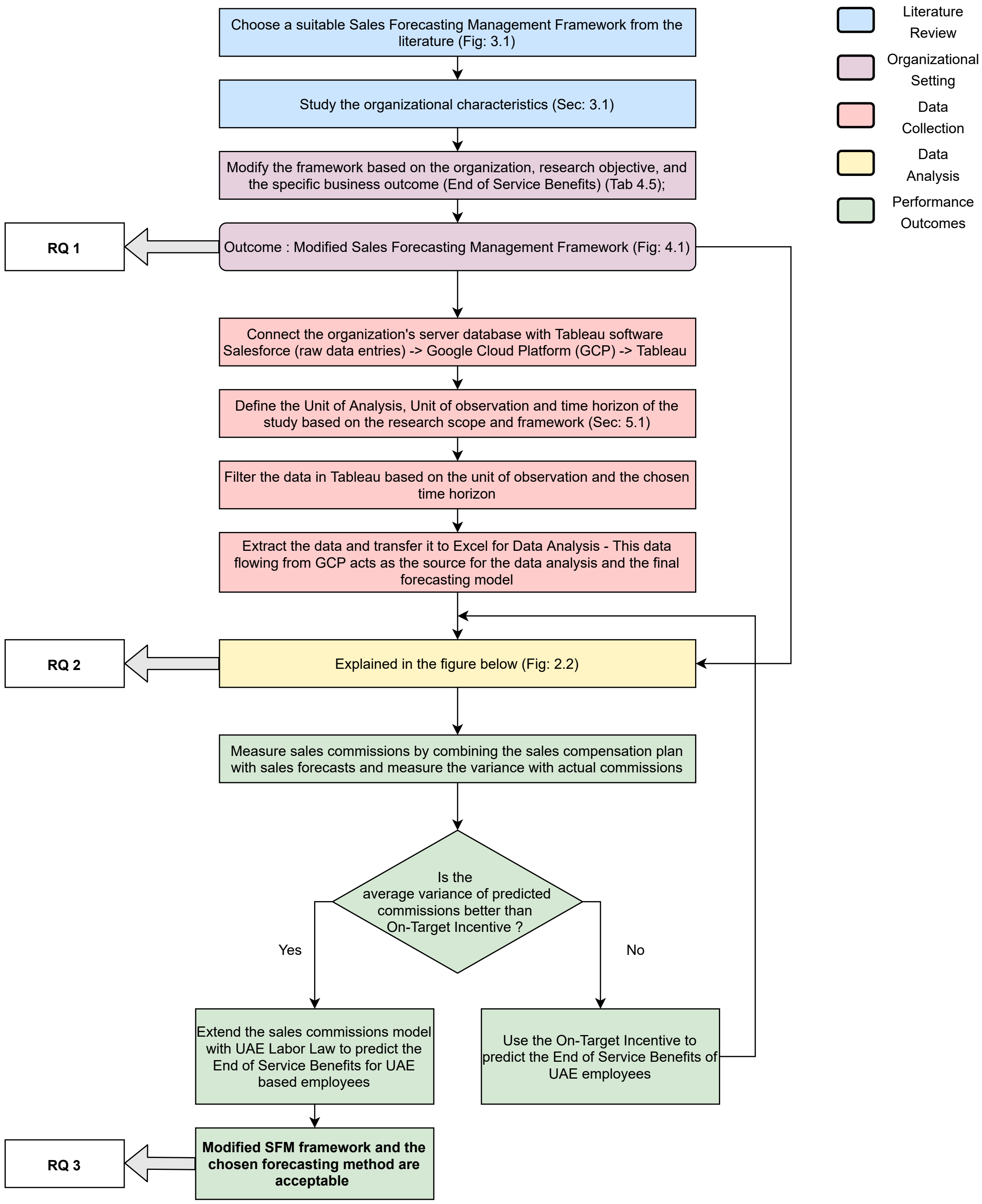

Figure 2.1: Research steps to answer the sub-questions

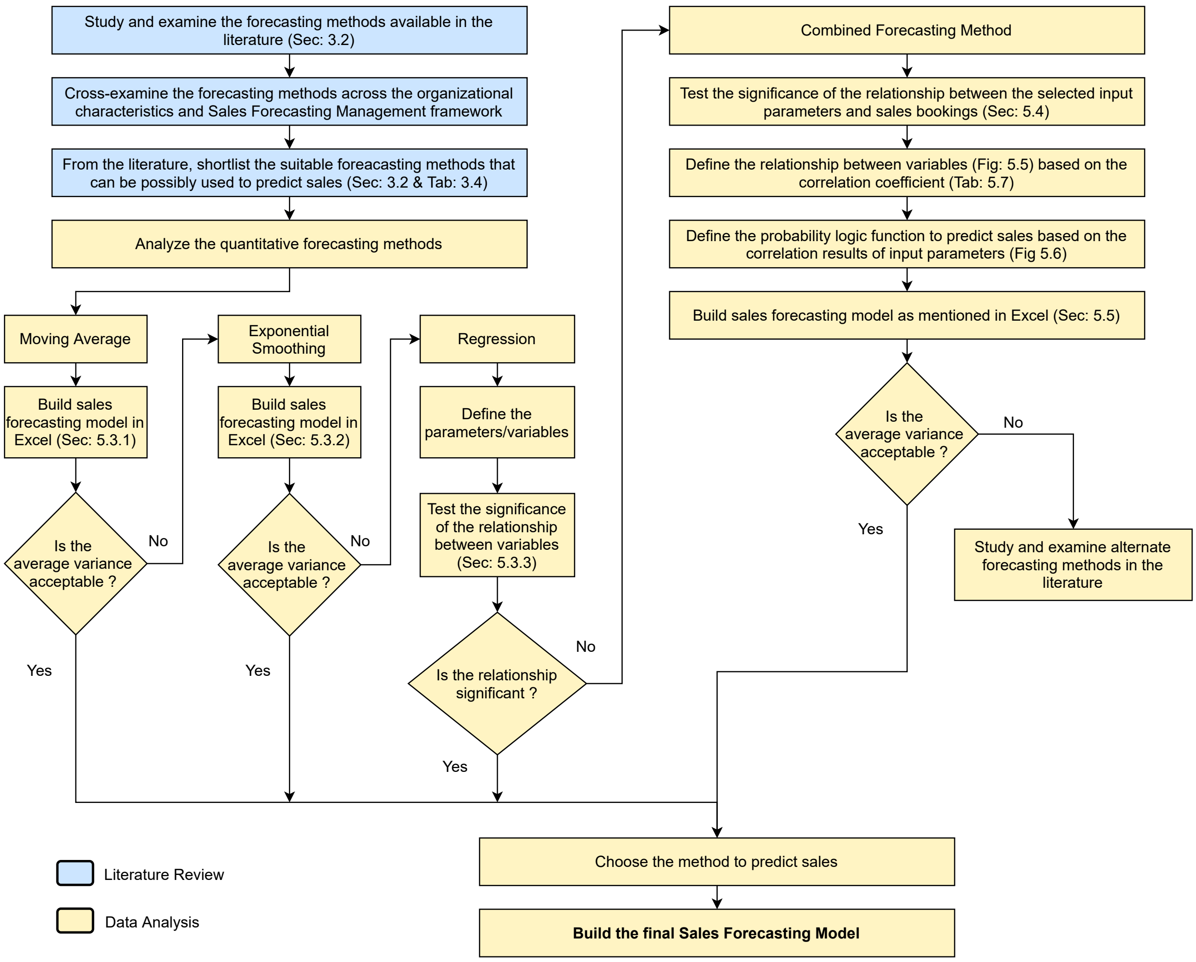

Figure 2.2: Data Analysis and the step-by-step procedure to choose and build the appropriate sales forecasting model

3
Literature Review

The research problem has been discussed in the previous chapter along with research questions and objectives. Based on this, different journals, articles, and books are explored to explain the theories that are required to carry out this study. This study is mainly focused on two parts - the framework that explains the sales forecasting management in an organization and the relevant forecasting methods which can be used to build the sales forecasting model. This chapter forms the key foundation for the next steps of the study.

3.1. Sales Forecasting Management

Sales Forecasting Management refers to the management of sales forecasting – an important business function within an organization. The sales forecasting function involves a myriad of processes that includes understanding the context of organizational characteristics, information systems and utilizing the proper forecasting technique based on the needs of the forecasters (Mentzer and Moon, 2004). Forecasting is a critical management function required by various departments within the organization. The organizations revise its business plan once in every fiscal year/quarter, and forecasting is the first step of the business plan (Moon et al., 1998). As mentioned in Sec. 1.1, the financial health of an organization depends on the performance of forecasts since the plan was predicated upon the forecast.

To understand sales forecasting management, it is important to distinguish forecasts vs plans vs targets. A sales forecast can be defined as “ a projection into the future of expected demand, given a stated set of environmental conditions” (Mentzer and Moon, 2004, Pg. 9). The plan is defined as “a set of specified managerial actions to be undertaken to meet or exceed the sales forecast” and the sales target is defined as “sales goals that are established to provide motivation for sales and marketing personnel” (Mentzer and Moon, 2004, Pg. 9). Sales forecasting is needed in a multitude of departments and the organization follows a cross-functional collaboration and ownership of the forecasts. In the paper (Mccarthy et al., 2006), the authors conducted a survey to study the evolution of forecasting practices by sending a web questionnaire to forecasting executives from 480 companies. Based on the results, the authors found that around 56% of the companies involved cross-functional teams in sales forecasting but the responsibility to develop the sales forecasts was observed to be sales and marketing (56%) followed by finance (15%) (Mccarthy et al., 2006). The sales forecasting needs of different departments within an organization are tabulated as follows:

Table 3.1: Forecasting Requirements by different departments within an organization (Mentzer and Moon, 2004)

Departments	**Needs for sales forecasting**
Sales	Setting goals for Sales employees
	Compensation Plan
Finance/Accounting	To predict and plan cost, profits, and capital needs on both corporate and divisional level
Production/Purchasing	Production planning schedule
	Development plans concerning suppliers, plants, and equipments
Logistics	To plan supply chain activities

3.1.1. Sales Forecasting Management Framework

This research started by performing a literature study of forecasting and finding as much as possible information about the current sales forecasting practices and the specific business process affected by sales forecasting. From the perspective of an organization, different factors contribute to sales forecasting performance. The authors (Davis and Mentzer, 2007) have proposed a Sales Forecasting Management (SFM) framework which links the organizational climate and capabilities to sales forecasting performance. The proposed sales forecasting management (SFM) framework can be found below:

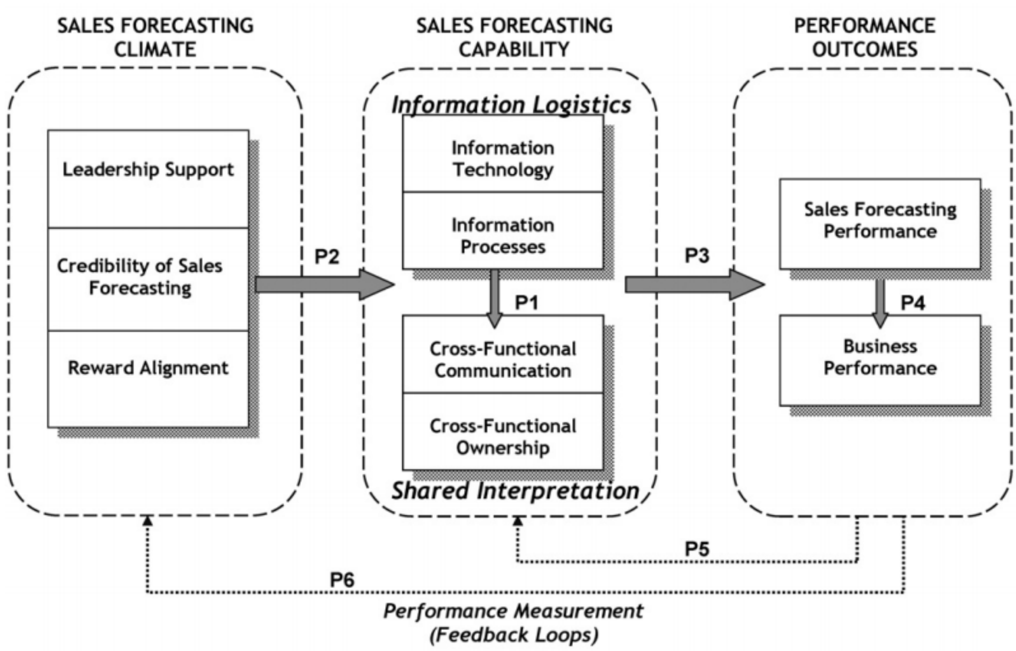

Figure 3.1: Sales Forecasting Management (SFM) Framework (Davis and Mentzer, 2007, Pg. 477)

1. **Sales Forecasting Climate** The organizational climate can be defined as "a set of measurable properties of the work environment, perceived directly or indirectly by the people who live and work in this environment and assumed to influence their motivation and behavior"(Al-Shammari, 1992, Pg. 30). One of the important dimensional factors of organizational climate is leadership support. The level of commitment of top-level management in the sales forecasting process has a significant effect on its performance (Moon et al., 2003). The top management involvement in the forecasting includes the approval of the forecasts and investigation to a lesser extent. The participation of executives in the investigation of forecasts increased the number of methods used for the forecasts and its objectivity which in turn increased the forecast accuracy (West, 1994). The paper (Durand, 2003) explains that having a high self-perception of a firm's performance has a negative effect on forecast accuracy while an organization's increased support of employee education has a positive impact on the accuracy. These findings are critical and top-level executives must be aware of the organizational factors that affect the forecast accuracy. It is evident that top-level management's involvement has a positive impact on forecast accuracy. Hence it becomes important to identify how the top-level executives can stimulate and improve forecasting performance. As mentioned in 3.1, sales forecasting is used to set goals for salespeople and to develop a sales compensation plan. Furthermore, the sales target and the incentives mentioned in the compensation plan set the climate and motivate the sales employees to excel and exceed the targets (Mentzer and Moon, 2004).

2. **Sales Forecasting Capability** Information Technology is a component that is used to enhance the quality of the business process and promotes organizational performance. These information systems include many software and enterprise-wide systems that help the organization to manage different business functions (Dewett and Jones, 2001) and sales forecasting management is not an exception. IT enables the generation of information, dissemination of information by serving as a communication channel and thus aids in cross-functional communication (Davis and Mentzer, 2007). In addition to

that, functional integration when developing sales forecasts is more beneficial for the organization. The components of the functional integration are Forecasting C3 – Communication, Coordination, and Collaboration. This helps the organization to reduce bias in forecasting, improve knowledge sharing between representatives of different departments thereby aiding in the development of superior forecasts (Mentzer and Moon, 2004). Finally, defining the environment of the company that affects the development and performance of sales forecasting is critical since it relates to organizational capability with the forecasting process (Mentzer and Moon, 2004). The companies can sustain or improve their competitive advantage by improving their unique capabilities. This includes both inside-out and outside-in capabilities. As mentioned in the paper (Davis and Mentzer, 2007), the organizational capabilities can be divided as Inside-Out (internal processes like manufacturing), Outside-In (external processes like marketing), and Spanning activities (both Inside-Out and Outside-In). Spanning activities include both the Inside-Out and Outside-In capabilities and forecasting is an important spanning activity. One of the key functions of the managers at a company is to perform inside and outside searches to discover asymmetries and increase the competitive advantage. To discover asymmetries and capabilities, it is important to understand which resources and capabilities are most central to the forecasting process and the place where they reside within the organization. Resources can be information about customers, divisions, and technologies; and capabilities can include the organizational structure and different aspects of sales/marketing (Miller et al., 2002). The Inside-Out and Outside-In activities that influence the sales forecasting process within the context of the organization will be discussed in detail in chapter 4.

3. **Performance Outcomes** In the article (Davis and Mentzer, 2007), the authors mention that linking the sales forecasting performance with a business outcome will provide superior value for the customers, and thereby the business. The performance outcome evaluation can include the internal company benchmarks like forecast accuracy goals or measuring customer needs/satisfaction (Davis and Mentzer, 2007). As mentioned in the section 1.2, the thesis evaluates the outcome/forecast accuracy of the prediction of End of Service Benefits which accounts for an important operational expenditure for the company. Additionally, the high performance of forecasting capabilities can improve the quality of business decisions since forecast accuracy has an effect on the organization's stock price and investment decisions.

As mentioned in the research objective section 1.2, the thesis focuses on modifying this sales forecasting framework according to the context of Palo Alto Networks. The sales forecasting climate characteristics, specifically the reward alignment depends on the product type, sales costs, profit of the company, customers, historical sales, etc. These characteristics can be explained by studying the product life-cycle stage of the company. Additionally, quantifying the sales forecasting framework is also an important research gap that is aimed to be fulfilled by this study. In order to quantify the sales forecasting performance, it is required to build a sales forecasting model. The literature study exhibited the correlation between the stage of the life cycle of a company with the forecasting methods used. The article (Chambers et al., 1971) explains how the decision-making process differs based on the life cycle stage of the company. Based on the above two reasons and the research objectives, a literature study was carried out to explain the Product Life Cycle (PLC) concept.

3.1.2. Product Life-Cycle Concept

To position the company in a stage, it is important to study the sales characteristics of the company along with its current objectives and strategies. The book (Kotler, 2016) proved to be the perfect literature explaining the Product Life Cycle(PLC) concept and its characteristics. The PLC concept helped the organization to perform planning & control and forecasting activities. Most of the PLC is usually bell-shaped and the curve comprises of four stages, namely – Introduction, Growth, Maturity, and Decline stage. Before discussing each stage of the PLC, it is essential to understand the product mix offerings, marketing objectives, and offerings of Palo Alto Networks.

Palo Alto Networks, founded in 2005, has been a pioneer of the cybersecurity industry. They offer different products that protect private and government entities from security breaches and cyberattacks. The products offered by Palo Alto Networks are segmented into three broad categories based on the functionality and use cases,

- **Strata** - It includes the myriad of products that are available as both physical and virtual machines or cloud services. The Next Generation Firewall (NGFW) is a physical appliance and VM-Series is a virtual machine. Some products like Panorama management are delivered both as physical appliances and virtual machines. In addition to that, strata include subscriptions like Threat Prevention, Global Protect, DNS, and Wildfire (Palo Alto Networks, 2019).

- **Prisma** - Palo Alto Networks acquired Redlock Inc, a cloud threat defense company in 2018. As part of the acquisition, the company worked to merge the strength of both parties' products in order to increase the competitive advantage in the market (Palo Alto Networks, 2018). By knowledge sharing and combining technologies Prisma Public Cloud (formerly Redlock) and Prisma Access (formerly GlobalProtect cloud service), the company provides security and compliance for user access, public cloud, in-line security for private and public cloud. This segment consists of futuristic products which are yet to penetrate the market and contributes very little in terms of the company's revenue.

- **Cortex** - This includes series of products such as Cortex XDR that provides security for operations, Autofocus that provides threat intelligence, Demisto for security orchestration, and Data Lake for secure data analytics (Palo Alto Networks, 2019).

Within the organization, Prisma and Cortex segments are combined and called Speedboat for administrative purposes. The below figure demonstrates the percentage of each segment's contribution to the company's total revenue from years 2016-2019.

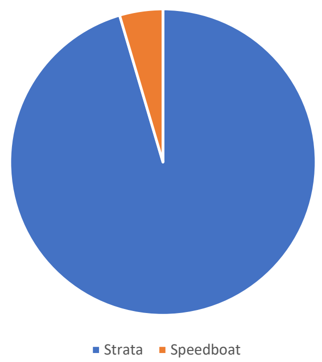

Figure 3.2: % Revenue by Product Segment (Single Source of Truth, 2021)

Cortex contributed 3.59% of revenue (2016-2019) whereas Prisma contributes 0.98% of the total revenue (2018-2019).

The below figure represents the characteristics and strategies across different stages of the PLC concept.

The characteristics and strategies of the PLC concept will be analyzed later in chapter 4 against Palo Alto Networks' characteristics and strategies to position the PLC stage for the company. The sales forecasting climate characteristics and the foundation for choosing a forecasting method are given by the Product Life Cycle (PLC) concept. The next step in the quantification of the framework is to choose an appropriate forecasting method. Hence the following part of the literature review focuses on the available methods in the literature using which the sales forecasting model can be built.

3.2. Forecasting Methods

The section consists of available forecasting methods in the literature. The article (Mccarthy et al., 2006) provides the results of the survey that explains the forecasting practices followed in business environments. The article also provides similar results as discussed above stating that sales are an important entity contributing nearly 80% of the information for forecast management with the sales team owning around 40% of the forecasts. The survey results indicate that companies utilized quantitative techniques for forecasting and showed a trend of higher satisfaction with quantitative than qualitative forecasting methods (Mccarthy et al., 2006). But in this study, both quantitative and qualitative methods are evaluated based on the outcome of the product life cycle concept which will be discussed in chapter 4. The below figure explains the different types of forecasting techniques available for predicting sales by comparing different articles.

	Introduction	Growth	Maturity	Decline
Characteristics				
Sales	Low sales	Rapidly rising sales	Peak sales	Declining sales
Costs	High cost per customer	Average cost per customer	Low cost per customer	Low cost per customer
Profits	Negative	Rising profits	High profits	Declining profits
Customers	Innovators	Early adopters	Middle majority	Laggards
Competitors	Few	Growing number	Stable number beginning to decline	Declining number
Marketing Objectives				
	Create product awareness and trial	Maximize market share	Maximize profit while defending market share	Reduce expenditure and milk the brand
Strategies				
Product	Offer a basic product	Offer product extensions, service, warranty	Diversify brands and items	Phase out weak products
Price	Charge cost-plus	Price to penetrate market	Price to match or best competitors'	Cut price
Distribution	Build selective distribution	Build intensive distribution	Build more intensive distribution	Go selective: phase out unprofitable outlets
Communications	Build product awareness and trial among early adopters and dealers	Build awareness and interest in the mass market	Stress brand differences and benefits and encourage brand switching	Reduce to minimal level needed to retain hard-core loyals

Table 3.2: Summary of Product Life-Cycle Characteristics, Objectives, and Strategies (Kotler, 2016, Pg. 179)

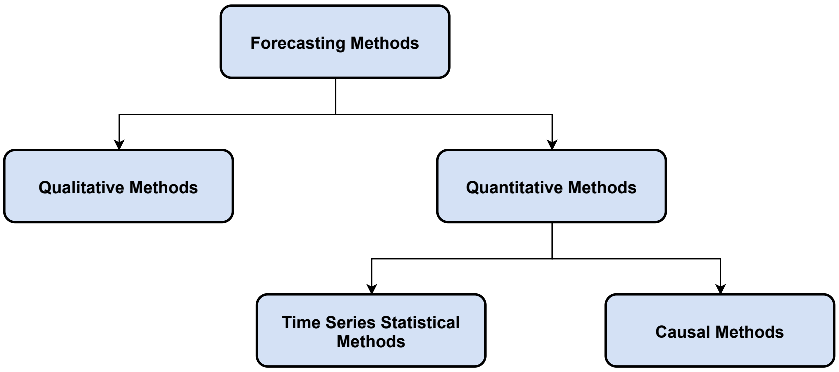

Table 3.3: Forecasting Methods

Based on the results of the first sub-question, the literature review and research scope are focused on both time series forecasting and qualitative technique which will be discussed in this section.

3.2.1. Quantitative Methods: Time Series Statistical Methods

A vast amount of literature has been analyzed to explain different time series forecasting models, understanding the advantages and disadvantages. This section provides more clarity about the measures to be considered to choose a suitable forecasting model. After going through the articles (Šečkute and Pabedinskaite, 2003) (Mccarthy et al., 2006) &(Chambers et al., 1971), the information about different models and their characteristics are analyzed and tabulated as follows.

Based on the characteristics of the company, the forecasting method will be shortlisted and tested for accuracy with historical and live data in chapter 5. But each method has been explained in detail in this section.

1. **Moving Average**
   The moving average is a simple method that is used to study and forecast the trends in the data. It is a time series built by considering the average of moving recent observations. But for every forecast, the number of data points remains constant. The moving average can be used to smooth the data, or for forecasting simple time-series variables. But in most cases, this method forms the basis for other complicated forecasting methods (Hyndman, 2011).
   The types of moving average include Two-sided Moving average, Centered Moving average, Moving averages with seasonal data, and Weighted Moving average. The two-sided technique is the simple one to smooth the randomness in the data and the centered moving average requires an odd number of observations to predict every forecast outcome. For data that retains repetitive seasonal characteristics, moving average with seasonal data is used to smooth the seasonality. Similarly in the weighted average method, appropriate weights called weight functions are given to the data such as the sum is one and symmetric. The result of this method is much smoother (Hyndman, 2011).

2. **Exponential Smoothing**
   The method of exponential smoothing forms the basis for many forecasting methods. It follows the concept where the weights of the older observations get decreased exponentially. The most common methods of exponential smoothing include Simple Exponential Smoothing, Holt's Linear, Damped Trend, and Holt-Winter's Methods (Exponential Triple Smoothing). If the data shows linear characteristics, simple exponential smoothing or damped trend methods are suitable. But in the case of a presence of a seasonal and trend component, exponential triple smoothing aids better forecasts (Hyndman et al., 2008). Excel has an in-built function for exponential smoothing called FORECAST.ETS. The syntax of this function is explained as follows (Microsoft, 2019):
   FORECAST.ETS(target date, values, timeline, [seasonality], [data completion], [aggregation])

   (a) Target Date - This represents the timeline at which you need to forecast a value. It can be a date, time, or other numeric. This is a required field.
   (b) Values - This contains the historical data or values which will be used to predict the future values. This is also a required field.
   (c) Timeline - This contains the range of timeline for the historical values. There should be a consistent step between each value and it cannot be zero. This is a required field.
   (d) Seasonality - Excel automatically detects seasonality. But we can choose it to be 0 if we don't want the seasonality function to be included. This is an optional field.
   (e) Data Completion - If there are values that are not supported by the consistent timeline, excel can support up to 30% of the missing data. This is an optional field.
   (f) The FORECAST.ETS function will aggregate multiple values that have the same timeline. By default (0), it will use the average of all the values with the same timeline but it can also be specified to use other functions such as SUM/COUNT. This is again an optional field.

3. **Regression**
   Regression is an advanced correlational technique. Correlation determines if and how two measured variables are co-related and regression is an extended technique to use the correlated variables for prediction. The simple regression model is given as follows (Rook, 2020):
   $y = b + mx + e$, where
   y = dependent variable/output
   x = independent variable/input
   b = y-intercept of the line
   m = slope of the line
   e = random error component/white noise
   The stronger the relationship between the variables, the more accurate the prediction will be. In excel, the regression function can be used by adding the Analysis ToolPak Add-in under the data analysis tab.

3.2.2. Combined Methods

In the article (Doyle and Fenwick, 1976), the authors explain that qualitative methods are used in case of the absence of historical data. But the usage of combining qualitative and quantitative methods has aided more accuracy in the forecasts. The sales Department composite method is a commonly used method where the inputs from sales employees are used to create a bottom-up forecast. It is seen that a salesperson will have a better intuition about the customer, their relationships, and their expertise in sales. In cases of sporadic sales, this method serves to be the most useful and it's also used for short to medium-term sales forecasts (Mishra and Prasad, 2004). In the chapter 5 of the thesis, a qualitative method of Sales Department composite will be used. It includes the estimates provided by the sales rep of each region. The variables will be studied to exhibit the correlational relationship and it is quantified to predict sales. These methods will be analyzed and used to predict the sales bookings forecast in the chapter 5.

3.3. Summary

The flow of the literature search is based on the problem statement, research objectives, and research questions that are mentioned in the chapter 1. The findings of the literature review on forecasting methods are explained in the table 3.4. The important factors that should be considered while choosing the forecasting methods are given as follows:

- Input data - One of the important inputs for the sales forecasting model is the historical sales made by the company. But each method requires a particular past set of sales data to make future predictions. This is an important factor to be considered since it determines if the organization has the available historical sales data to build the forecast model.
- In addition to the input data, each forecasting method can make predictions at different time horizons. Some methods can only make sales predictions for a short period of time when compared to others. Based on the requirement of the organization, the forecasting methods should be chosen.
- The table also includes the advantages and disadvantages of each method to validate its efficiency and to understand its limitations.

The above-mentioned forecasting methods will be validated and tested later in the thesis in chapter 5. Further, the table 4.5 explains the direction of the literature review and its connection with the research questions and methodology.

Table 3.4: Results from literature (Šečkute and Pabedinskaite, 2003) (Mccarthy et al., 2006)&(Chambers et al., 1971)

METHODS	**TIME HORIZON**	**REQUIRED DATA**	**FREQUENCY OF USE**	**ADVANTAGES**	**DISADVANTAGES**
Moving Average	Short horizon <= 3 months	Sales history <2 years in case of absence of seasonality Sales history >= 2 years in case of presence of seasonality	Frequently used for short-term forecasts	Simple to use Low cost	Too simple and does not model the seasonality trends in the data
Trend-Line Analysis	Short horizon <= 3 months	Sales history >= 2 years	Frequently used for short-term forecasts	Simple to use Low cost	Not suitable when there are dynamics in the data, assumes regularities in the past will appear in the future as well
Exponential Smoothing	Mid-horizon 4 months - 2 years	Sales history >= 2 years	Frequently used for short-term forecasts	Fast, efficient and simple to understand	Has different types of models Some models take more computational time and required extensive data
Regression	Long-horizon >2 years	Sales history >= 2 years	Frequently used for long-term forecasts	The explanatory method explains the relationship between the dependent and independent variables	Complicated if there are more inter-relationships between variables and requires extensive data
Box-Jenkins / Arima	Short horizon <= 3 months	Sales history >= 2 years	Less frequently used when compared to other methods	The accuracy of the model is high, and it also takes small errors into account	Complicated and more time-consuming when compared to other methods

Research Objective	Research Questions	Search Methodology	Results of the Literature Review
To propose a modified Sales Forecasting Management framework based on the characteristics and context of the organization.	**RQ1**. What are the characteristics of a high-tech company (Palo Alto Networks) that influence sales forecasting management?	To search for scientific articles, papers, journals that connects organizational factors with sales forecasting management	**Figure 2.1:** Sales Forecasting Management (SFM) Framework from the article (Davis and Mentzer, 2007, Pg. 477)
To propose a modified Sales Forecasting Management framework based on the characteristics and context of the organization.	**RQ1**. What are the characteristics of a high-tech company (Palo Alto Networks) that influence sales forecasting management? **RQ2**. What is the appropriate forecasting technique that predicts sales for the given high-tech industry (PaloAlto Networks)?	The aim of this search is twofold: a) To choose a conceptual framework that explains the elements such as sales/costs/profits that are important to frame the reward alignment for sales employees b) To choose a concept whose results can be used to interpret the appropriate sales forecasting method	**Table 2.2:** Product Life-Cycle Characteristics, Objectives, and Strategies (Kotler, 2016, Pg. 179)
To investigate ways to quantify the modified Sales Forecasting Management framework that capturethe characteristics of the organization.	**RQ2.** What is the appropriate forecasting technique that predicts sales for the given high-tech industry (PaloAlto Networks)?	The aim of this search is to find the relevant forecasting methods in the literature than can be used to build a quantitative sales forecasting model	**Table 2.3:** Results from literature (Šeckute and Pabedinskaite, 2003) (Mccarthy et al., 2006)&(Chambers et al., 1971)

Table 3.5: Summary of Literature Review

4

Organizational Setting

This chapter provides the modified SFM framework suitable for the organizational context. Followed by that, the characteristics, and strategies are analyzed to position the product life cycle stage of the company. Finally, the organizational characteristics - sales compensation structure and the UAE labor law that influences the final forecasting model are discussed and analyzed. The results of this chapter provide the answer to sub-question 1.

4.1. Modified Sales Forecasting Management (SFM) Framework

The framework is redefined to fit the organizational setting of Palo Alto Networks and the scope of the thesis. The components of the SFM framework are defined below based on the organizational setting:

4.1.1. Sales Forecasting Climate

The sales forecasting climate includes the characteristics of the organization which has an impact on sales forecasting capability and in the measurement of the performance outcome. As mentioned in 1.4, it is important to incorporate the effect of organizational characteristics in sales forecasting of the final quantified simulation model. The components of the forecasting climate are explained below:

1. Organizational Characteristics:
   When referring to the current organizational setting, the forecasting model of End of Service benefits includes both internal and external organizational factors. The sales compensation structure, product life-cycle stage of the company are the internal factors and the UAE labor law is the external factor that has a direct influence on the employee's end of service benefits. Additionally, the business is noticing a pattern in the bookings based on the seasonality of customer spending (Palo Alto Networks, 2019) and it is important to validate if seasonality is an important factor when modeling the bookings forecast for UAE based sales employees. This will require the forecasting model to incorporate both internal and external factors as explained before. The sales compensation structure and the UAE labor law will be explained in sections 4.3 and 4.4 respectively.

2. Leadership Support
   Based on the results and observations of the sales forecasting model in chapter 5, the thesis reflects to provide improvements/suggestions to top-level management to improve the sales forecasting performance. It has been represented as the feedback loop of the modified SFM framework. Specific to the thesis, the company has a benchmark regarding forecast accuracy. The variance of the forecast vs the initial business plan of the fiscal year should be as less as $\pm$ 0.5 by the last quarter. This high demand for forecast accuracy is due to the impact of forecasting performance on the company's stock price value. This shows that top-level management's interference in the forecasting process is evident and crucial. The feedback for the top-level management will be explained in the chapter 6.

4.1.2. Sales Forecasting Capability

This is an important component of the thesis. The sales forecasting capability is divided into three sections – Information Logistics, Cross-Functional communication, and Forecasting technique.

1. Information Logistics:
The information technology systems that are utilized for the thesis are listed below along with their process:

    - **Salesforce:** This Customer Relationship Management (CRM) software helps the sales employees to record their bookings data.
    - **Tableau:** This software uses Salesforce bookings as the data source to visualize, understand and analyze data.
    - **Google Cloud Platform (GCP):** This is a data storage platform that stores and connects a large amount of data that flows within the organization's infrastructure. The entries/data created by the employees in Salesforce are stored in the GCP data server which is used for data collection and analysis in chapter 5.
    - **SAP Employee Central Payroll (ECP):** SAP ECP is accounting software and a payroll system that provides an overview of the general ledger of the company and records all the business transactions of the company. The employee's salaries and commissions are recorded in the general ledger.
    - **Excel:** Finally, excel is used to build the forecasting model that predicts sales/bookings and end of service benefits.

2. Cross-functional Communication:
To perform the case study at Palo Alto Networks and develop a forecasting simulation model predicting End of Service Benefits, cross-functional collaboration, and knowledge sharing between different departments served importantly. The departments that are involved in the forecasting process are mentioned as follows:

    - **Sales Planning:** Sales planning keeps track of an employees' bookings track record. Collaboration with this department is important to understand the sales compensation structure.
    - **Sales Operations:** Sales Operations has the responsibility to track the sales data for trends and modifying the sales targets. This team uses the information systems on a daily basis and is considered to be an expert. Hence the collaboration with this department is crucial to understand and effectively work with information systems like Salesforce and Tableau.
    - **Sales Finance:** The main responsibility of the department is to plan, allocate and keep track of the operational expenditures of the sales team. The key functions involve financial planning, forecasting, and analysis. The department holds the ownership of different forecasts including the EOSB forecast model.

    For the thesis, knowledge sharing and cross-functional communication are essential but cross-functional ownership is not seen.

3. Forecasting technique
This is an important and final step in the sales forecasting capability component of the SFM framework. Based on the characteristics and above-mentioned capabilities of the organization, a suitable forecasting technique should be chosen to improve the sales forecasting performance. The inputs required for the forecasting model, data collection based on the characteristics of the company will be the initial step in choosing a forecasting technique. These forecasting methods are analyzed and the most appropriate method that aids in improving sales forecasting performance is chosen. This is discussed in detail in the next chapter 5.

4.1.3. Performance Outcome

Sales forecasting has an impact in predicting the end of service benefits for the employees. On an organizational level, the End of Service Benefits (EOSB) accounts for an important operational expenditure of the company, the employee earnings. And with the company being public listed, accuracy in predicting its operational expenditure influences its share price (Montgomery, 2002). In the redefined framework, the effects of sales forecasting performance in predicting the end of service benefits are studied. And the final forecasting model captures the effect of sales forecasting, organizational characteristics on the EOSB quantitatively as mentioned in the chapter 6. Based on Palo Alto networks' organizational setting and scope of the thesis, the SFM framework is modified as mentioned below:

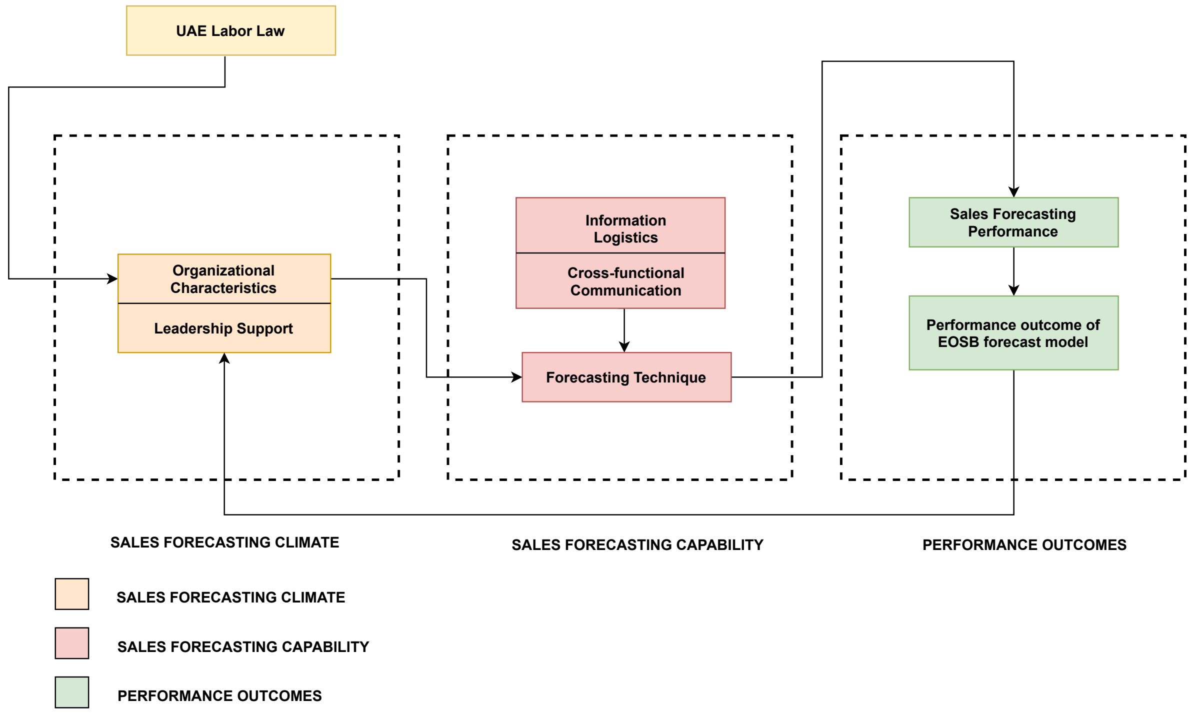

Figure 4.1: Modified Sales Forecasting Management (SFM) Framework
Note: The framework is constructed through literature review and organizational setting and based on the paper (Davis and Mentzer, 2007, Pg. 477)

4.2. Product Life Cycle Stage of the Company

4.2.1. Characteristics of the organization

This section discusses the characteristics, objectives, and strategies of the company to answer the first sub-question – characteristics of the company that influence the sales forecasting management. The characteristics are compared with the product life cycle concept as mentioned in 3.1.1. The data from the yearly financial reports of the company are collected to analyze product life cycle characteristics. The consolidated data from the financial reports are given below:

1. Sales

	2019	2018	Change		2018	2017	Change		2017	2016	Change	
	Amount		Amount	%	Amount		Amount	%	Amount		Amount	%
					(dollars in million)							
Revenue/Sales	2,899.6	2,273.6	626.0	**27.5%**	2,273.6	1,755.1	518.5	**29.5%**	1,755.1	1,378.5	376.6	**27.3%**
Cost	808.4	645.1	163.3	**25.3%**	645.1	476.4	168.7	**35.4%**	476.4	370.0	106.4	**28.8%**
Profits	2,091.2	1,628.5	462.7	**28.4%**	1,628.5	1,278.7	349.8	**27.4%**	1,278.7	1,008.5	270.2	**26.8%**
No. of Customers	40881	36138	4743	**13.1%**	36138	29438	6700	**22.8%**	29438	24056	5382	**22.4%**
					(dollars in thousands)							
Cost/Customer	19.8	17.9	1.9	**10.8%**	17.9	16.2	1.7	**10.3%**	16.2	15.4	0.8	**5.2%**

Table 4.1: Consolidated financial data 2016-2019 (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

The financial report and the sales trend show a steady increase in sales across every fiscal year from 2016-2019. The company has three major theatres/divisions namely – America, Europe, Middle East, and Africa (EMEA), and Asia-Pacific (APAC). The sales trend for each theatre is analyzed below:

The financial report and the sales trend show a steady increase in sales across every theatre/division through the fiscal year from 2016-2019. This shows similar characteristics across every theatre of the global company. Further, the characteristics of the company are assumed to be suitable for each theatre.

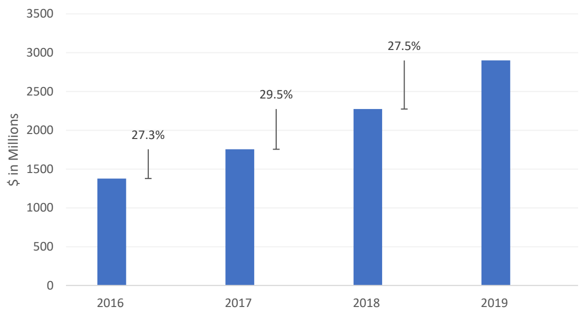

Figure 4.2: Sales Trend 2016-2019 (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

Theater	2019	2018	Change		2018	2017	Change		2017	2016	Change	
	Amount		Amount	%	Amount (dollars in million)		Amount	%	Amount		Amount	%
America	1,982.3	1,558.7	423.6	**27.2%**	1,558.7	1,230.6	328.1	**26.7%**	1,230.6	973.2	257.4	**26.4%**
EMEA	564.8	439.6	125.2	**28.5%**	439.6	320.3	119.3	**37.2%**	320.3	247.1	73.2	**29.6%**
APAC	352.5	275.3	77.2	**28.0%**	275.3	204.2	71.1	**34.8%**	204.2	158.2	46.0	**29.1%**

Figure 4.3: Consolidated sales data across each theatre (2016-2019) (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

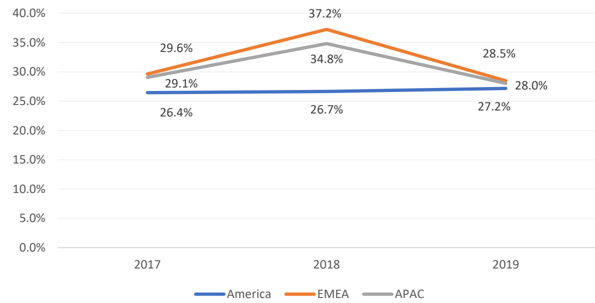

Figure 4.4: Sales Trend across each theatre 2016-2019 (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

2. Cost
   As seen in 4.1, the cost per customer shows a steady increase through the fiscal years 2016-2019. But on the other hand, the percentage of cost in the overall revenue has remained more or less stable as shown below in 4.2. Hence it can be concluded that the company experiences an average cost per customer.

	2019	2018	2017	2016
	(dollars in million)			
Revenue/Sales	2,899.6	2,273.6	1,755.1	1,378.5
Cost	808.4	645.1	476.4	370.0
% of Cost in total Revenue	**27.9%**	**28.4%**	**27.1%**	**26.8%**

Table 4.2: Consolidated financial data explaining %cost in total revenue (2016-2019) (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

3. Profits
   As mentioned in 4.1, there is a steady increase in profits from years 2016-2019. Below, there is a graph explaining the profit trend.

4. Customers
   Palo Alto Networks has a wide portfolio of customers from service providers, medium to large enterprises, and governmental entities. As per the financial report, not a single customer has accounted for more than 10% of the total revenue which shows the strong portfolio of customer base (Palo Alto

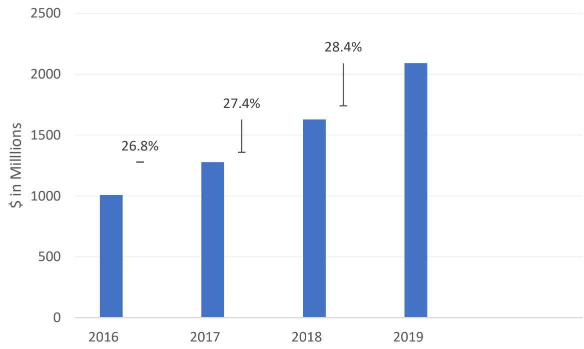

Figure 4.5: Profit Trend through 2016-2019 (Palo Alto Networks, 2017),(Palo Alto Networks, 2019)

Networks, 2019). The demand for the cybersecurity industry has increased in the past years and the Compound Annual Growth Rate (CAGR) is expected to grow at 10.9% from 2021 to 2028. With an increase in sophisticated cyberattacks, the proliferation and advancements of technologies are required in this industry and will be reflected in future products (Grand View Research, 2020). This shows that the customer should be in the middle majority category.

5. Competitors
   Currently, the competitors of the company fall into the following arena (Palo Alto Networks, 2019):

   - Large enterprises – Companies like Cisco systems have a well-established brand name, better brand positioning, and customer base. Due to the experience, the companies will also tend to have better economies of scale making their production more efficient and thus reducing the costs.
   - Independent Security Vendors – Companies like Symantec and Checkpoint might offer a better product mix and endpoint security products.
   - Other small and large enterprises compete with specific products or features provided by Palo Alto Networks

   In addition to that, an increase in demand is expected in the cybersecurity industry which will attract many new start-ups and other companies. The company identified around 40,261 suspicious registered domain names in March 2020. The increasing concerns about cybersecurity will fuel future market growth (Grand View Research, 2020) and increase the number of competitors.

4.2.2. Marketing Objectives and Strategies of organization

1. Marketing Objective
   The company takes measures to increase brand awareness, increase the customer base and improve brand reputation. It organizes many activities across different communication channels like social media and advertising to increase brand awareness. The company also organizes a cybersecurity conference called “Ignite” every year. This shows that the company is organizing varied activities to increase the channel partners in the pipeline and ultimately to maximize the market share (Palo Alto Networks, 2019).

2. Product
   As mentioned in section 3.1.2, the company is taking different measures to diversify its products. Being a leader in the cybersecurity industry, since its foundation, the company has also acquired nearly 16 companies (Palo Alto Networks Acquisitions, 2021). This shows that the company is clearly trying to diversify its products and improve its brand reputation.

3. Distribution
   The company has a two-tier indirect fulfillment business model where it sells its subscriptions and support via channel partners and distributors. This is one of the important reasons for the company to take marketing activities to build a strong distribution channel. As mentioned in the marketing objective section, the company organizes activities to build more intensive distribution since its also part

of its business model. One such example is NextWave Channel Program which is focused on building strong relationships with distributors and resellers. In addition to that, the company also provides a training program for sales and technical professionals of business partners (Palo Alto Networks, 2019)

4. Communications
As mentioned in the section Marketing Objective, the company's main focus and strategy are to increase brand awareness in the mass market.

Finally, the characteristics, objectives, and strategies of the company are compared against 3.2 to identify the product life cycle stage for the company.

Table 4.3: Summary of Product Life-Cycle Characteristics, Objectives, and Strategies (Palo Alto Networks, 2017),(Palo Alto Networks, 2019), (Grand View Research, 2020) & (Palo Alto Networks Acquisitions, 2021)

	Introduction	***Growth***	***Maturity***	***Decline***
Characteristics				
Sales			X	
Costs		X		
Profits		X		
Customers			X	
Competitors		X		
Marketing Objectives		X		
Strategies				
Product			X	
Distribution			X	
Communications		X		

5. Result
This shows that the company exhibits the characteristics of both growth and maturity and hence lies in between the growth and maturity stages.

4.3. Sales Compensation Structure of the Company

The sales compensation structure is an integral part of the SFM framework that affects the sales forecasting capability and also has a direct impact on predicting the business outcome (EOSB). The sales forecasting model and the extended version of the EOSB model contain different variables that are defined and derived from the compensation plan. This shows the importance of the sales compensation plan in the overall Sales Forecasting Management (SFM) framework. The main components of the sales compensation plan are defined below:

4.3.1. Structure

The overall structure of the sales compensation is defined by two different quotas. Each quota has a territory and product defined. This is a combination of products, segments, and roles of the employee. As mentioned in section 3.1.2, Palo Alto Networks offers a wide range of products that can be classified into two broad categories – Strata and Speedboat. The speedboat includes Cortex and Prisma products(Palo Alto Networks, 2021). The product classification for the current fiscal year is mentioned in the figure attached in the confidential appendix.

Based on the classification, two quotas are defined as follows(Palo Alto Networks, 2021):

- Quota 1: The bookings of the products under the category Strata are considered for attaining the quota 1 target. The Total Contract Value (TCV) of the products is taken into account.
Note: Total Contract Value (TCV) - It measures the worth of the contract after it's being executed, including recurring revenue and contract/service fees.

- Quota 2: The bookings of the products under the category Speedboat are considered for attaining quota 1 target. The Annual Contract Value (ACV) of the products is taken into account.

Note: Annual Contract Value (ACV) - It measures the worth of the annual/yearly revenue generated by the customer contract. ACV = TCV/Total years in contract

In addition to the product classification, the role of the employee determines the quota target. In this thesis, the scope of the role is restricted to sales employees, mentioned as Direct Quota Carrying (DQC) within the company. The salary of DQC employees is based on fixed base salary and a varied On Target Incentives (OTI)(Palo Alto Networks, 2021). The incentives are explained in detail in the following section.

4.3.2. Incentives

This section explains the incentives provided for the employees based on which the commissions of the employees can be derived and predicted.

The target quota (Quota 1&2) and the On Target Incentives (OTI) for the employees are defined by the managers in collaboration with the compensation planning team. The Base Compensation Rate (BCR) is defined as follows(Palo Alto Networks, 2021):
BCR = OTI/Quota

The commissions are dependent on different variables as defined below(Palo Alto Networks, 2021):

- Hardware Bookings (P) - It is defined as the initial value of the hardware product.
- Initial (I) - It is defined as the initial value of subscriptions/support services provided along with the hardware product.
- Multi-year (MY) - It is defined as the value of subscriptions/support services that will be incurred by the customer in the future.

Based on the above-mentioned variables, the base incentives and additional incentives are defined (Palo Alto Networks, 2021):

- Base Incentives - There are two base incentives,
  - P+I - This is equivalent to the base compensation rate (BCR).
  - Multi-year (MY) - This is equivalent to x*BCR (the rate is mentioned as x due to confidentiality reasons)
- Additional Incentives - The additional incentives are applicable only for Speedboat renewal bookings. Renewal defines the extension of an already available contract by the customer.It is defined as follows: Additional Incentives (Renewals) = y*BCR (the rate is mentioned as y due to confidentiality reasons)

Finally, there is an acceleration in commissions for employees. When the employee reaches 90% of the target bookings in both Quota 1 and Quota 2, the BCR is accelerated at a rate predefined by the sales planning team(Palo Alto Networks, 2021).

The Sales Compensation Structure is consolidated and tabulated which can be found in the confidential appendix.

4.4. UAE Labour Law

UAE Labor Law is an outside-In capability that affects the final forecasting model of End of Service Benefits. For the research, the scope of the thesis is limited and geographically delineated to the region United Arab Emirates (UAE) that comes under the region Middle East (MEA) of the theatre Europe, the Middle East, and Africa (EMEA) at Palo Alto Networks. The EOSB is affected by article 134 of UAE Federal Law which is stated below:

“Without prejudice to the provisions of certain laws on the pensions and retirement benefits granted to workers in certain establishments, end of service gratuity shall be calculated on the basis of the last wage due to monthly, weekly and daily-paid workers, and on the basis of the average daily wage set forth in Article 57 hereof for the workers getting paid by the piece. The wage used as a basis for calculating the end of service gratuity shall not include payments made to the worker in rem, housing, transport and travel allowance, overtime pay, representation allowance, cashier’s allowances, children education allowance, allowances for recreational and social services, and any other bonuses or allowances.” (Laws, 2001, Pg. 37)

Table 4.4: Consolidated data of UAE Labor Law for End of Service Benefits (Laws, 2001)

Years of Service (X)	***Entitled Gratuity Pay***
X<1	Not entitled to any gratuity pay
1<X<3	(1/3) of the 21-days gratuity pay
3<X<5	(2/3) of the 21-days gratuity pay
X>5	Full 30-days gratuity pay

4.5. Summary

The below table 4.5 summarizes the characteristics that are explained in this chapter and compares each one of them with actual Sales Forecasting Management (SFM) Framework (Davis and Mentzer, 2007) 3.1 with the modified framework as mentioned in the figure 4.1. The framework has three main parts - Sales Forecasting Climate, Sales Forecasting Capability, and Performance Outcomes. The climate includes the organizational characteristics/elements that are relevant to Palo Alto Networks and the outcome measured (End of Service Benefits). The leadership support and credibility of sales forecasting are similar to the original framework as mentioned in (Davis and Mentzer, 2007), but the element, the sales compensation structure is modified based on the organizational setting. Furthermore, the product life cycle stage of the company is an additional organizational characteristic studied to improve the sales forecasting capability. Finally, UAE Labor law is an external factor included in the modified framework as it affects the final outcome of End of Service Benefits.

The information logistics and cross-functional communication components of sales forecasting capability remains similar to the original framework but the forecasting technique is an additional component included as the thesis aims to validate the framework by building a quantified sales forecasting model.

Finally, the performance outcome stage of the framework is similar to the original SFM framework, but the specific business outcome measured in the thesis study is the End of Service Benefits as it is a significant operational expenditure related to employee earnings. The sales forecasting model is built based on the modified Sales Forecasting Management (SFM) framework and its forecasting performance impact is measured on the business outcome.

This chapter provides an overview of the characteristics that influence the sales forecasting management and the final forecasting model of End of Service Benefits. The influence of the characteristics will be quantified and studied in the next chapter to choose the appropriate forecasting method.

Sales Forecasting Component of the framework	Component	Modified Sales Forecasting Management (SFM) Framework (Figure: 4.1)	Comparison with original Sales Forecasting Management (SFM) Framework (Figure: 2.1)
Sales Forecasting Climate	Sales Compensation Structure	Sales Compensation Structure mentions the compensation structure specific under the following context: Organization, Fiscal year (2021), Product Classification (Strata/Speedboat)	Based on the incentives target/reward alignment, the framework suggests that pre-set incentive targets will have an effect on the sales outcome of the business which also undermined the effective sales forecasting performance.
	Product Life Cycle (PLC) Concept	Product Life Cycle (PLC) Concept is explained to understand product classification required for reward alignment and to choose forecasting method for the uantification of the model.	NA - This component in not available but it is specifically added in the modified framework since the thesis aims to quantify the framework
	UAE Labor Law	This is an external component which influences the forecasting performance of the business outcome (End of Service Benefits)	NA - The business outcome is generic but UAE Labor law is studied specifically to measure the performance outcome of End of Servoce Benefits
	Leadership Support	The impact of the sales forecasting performance on business outcome have generated useful insights for the top-level management. This feedback loop is explained in chapter 5 of the thesis.	The framework suggests that leadership support encourages sales forecasting practices and has a positive effect on the performance outcome
	Credibility of Sales Forecasting	This is not included as a component in modified framework but it has been explained in the final chapter as a reflection.	It refers to the reliability of the forecasting practices in an organization which is influenced by the sales force's expertise, confidence in his estimates, organizational structure/design etc,.
Sales Forecasting Capability	Information Logistics	Similar to original SFM framework	A firm's information process and IT infrastructure that supports dissemination of information which has an effect on the sales forecasting performance
	Cross-functional Communication	Similar to original SFM framework	Cross-functional communication and ownership facilitates free flow of inforation between different teams that makes the sales forecasting capability more superior.
	Forecasting technique	This is specific to modified framework based on the research objective of the thesis (to quantify the SFM framework and measure the sales foreacsting performance)	NA
Performance Outcome	Sales Forecasting Performance	Similar to original SFM framework	Evaluating the effect of sales foreacsting climate & capability on forecasting performance
	Performance outcomes	Evaluation of internal company benchmarks - forecast accuracy of End of Servcice Benefits	Evaluation of internal company benchmarks such as forecast accuracy goals

Table 4.5: Comparison of SFM framework in the literature against the modified SFM framework (Davis and Mentzer, 2007)

5

Sales Forecasting Technique

This chapter covers the data collection method, evaluation of different forecasting methods in the literature to predict sales. It is a crucial step of the thesis since it explains the relationship between different variables in sales forecasting under a high-tech organizational setting. The sales predicted using each forecasting method are measured against the recent sales data of the company. The variance between the actual sales and the predicted sales/bookings is measured to choose the most appropriate forecasting technique. The results of this chapter provide the answer for sub-question 2.

5.1. Data Collection

The approach of data collection is different for different fields of study, depending on the required information. The most critical objective of data collection is ensuring that information-rich and reliable data is collected for statistical analysis so that data-driven decisions can be made for research. Data Collection is an important step in research. The following elements of research design are revisited to define and retrieve the required data.

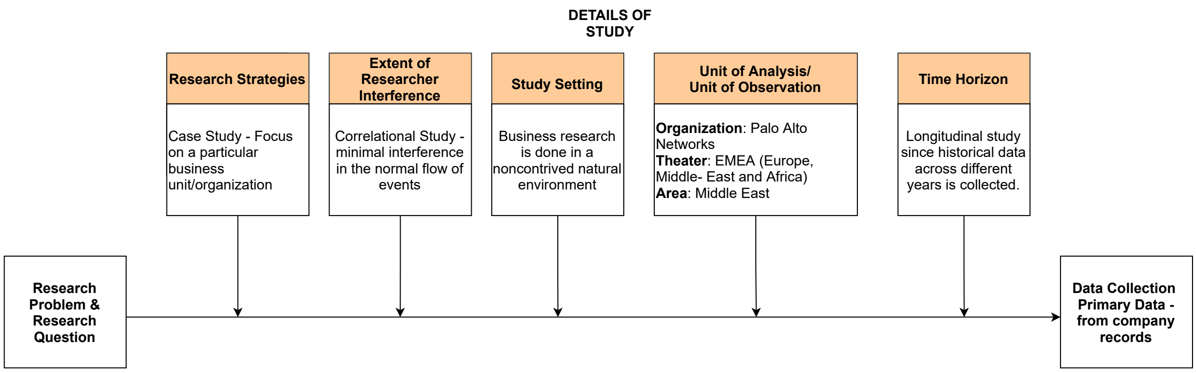

Figure 5.1: Elements of Research Design
Note: The design is constructed based on the organizational setting and the book (Sekaran and Bougie, 2016)

Before starting with the data collection method, the source of data and the elements of the research design are explained.

1. **Data Source**
   As mentioned in 4.1.2, the bookings made by every sales employee are recorded in Salesforce as opportunities. An opportunity has many details/measures that include the account name of the customer, account owner, account theatre, sales pipeline stage, an opportunity created date, closed date, PI, MY and total amount, etc. This data from Salesforce has been stored in the company live records called GCP Live Data. It acts as the source of data for all the analysts across the organization.

2. **Research Strategy**
   As mentioned in the chapter 1, a detailed case study is done in Palo Alto Networks, a high-tech organization in order to examine the SFM framework under the organizational setting and quantifying the framework under the perspective of different forecasting methods.

3. **Researcher Interference**
   This is a descriptive correlational study where the research is carried out in a natural environment with minimal interference. Hence the main aim is to identify the relevant variables, collect the relevant data, and analyze them to come up with results (Sekaran and Bougie, 2016).

4. **Study Setting**
   The research is a correlational study is done in a non-contrived setting.

5. **Unit of Analysis**
   The unit of analysis for the study is the organization, Palo Alto Networks but the unit of observation defines the unit described in the data-set (Sekaran and Bougie, 2016). It is explained as follows. This is a crucial element for data collection which also defines the scope of the thesis. The historical bookings are the data required to build the forecast model and to predict EOSB. But the following filters are applied before extracting the organization's bookings data:

   (a) Theater - As explained in chapter 4, the sales bookings relevant to Europe, Middle-East, and Africa (EMEA) are filtered.

   (b) Area - The area is filtered to the Middle East based on the scope of the business outcome measured.

   (c) Opportunity Stagename - The stagename for the historical data is either Closed-Won or Closed-Lost. In order to get only the historical bookings that were successful, the stagename of the data is filtered to Closed-Won.

   (d) Opportunity Type - Based on the compensation structure, the opportunity type is only filtered to record Initial Business and Expand Business.

   (e) Fiscalquarter - The historical data from the year 2018-2020 are collected to predict the bookings made in the year 2021.

   (f) Employee - Finally, based on the scope and the compensation structure suitable for the sales representatives, the bookings made by the Direct Quota Carrying of the Middle-East region are filtered.

   The raw data flowing from salesforce is filtered, visualized, and collected using the data management tool, Tableau as mentioned in chapter 4. This filtered historical bookings data is the unit of observation to predict the future bookings of the fiscal year 2021.

6. **Time Horizon**
   The historical data is recorded and analyzed across multiple points of time. The prediction of sales bookings is also made across the months in the fiscal year 2021. Hence the case study is longitudinal.

Finally, since Strata contributes to 95.42% of sales as mentioned in 3.2, with Strata and Speedboat having different compensation structures, the data collection and analysis is done based on Strata bookings.

Based on the above research design and the scope of the thesis, the primary data is collected using Tableau by connecting the organization's server database - Google Cloud Platform. The raw data is filtered based on the above-mentioned unit of observation. Finally, the data is extracted and transferred to Excel for analysis as discussed in section 5.2.

In the book (Chambers et al., 1971), the authors have provided the relationship of forecasting techniques based on the product life cycle stage of the company. As a result of 4.3, it is observed that the organization exhibits product life cycle at both growth and steady stages. Hence based on the (Chambers et al., 1971) and the chapter 3 both quantitative and qualitative methods are evaluated.

5.2. Data Analysis

The extracted bookings data is analyzed on a granular level to track the trend, seasonality of the bookings made by each employee (A-E) across every month from the fiscal year 2018 to 2020.

The bookings trend can be visualized as follows:

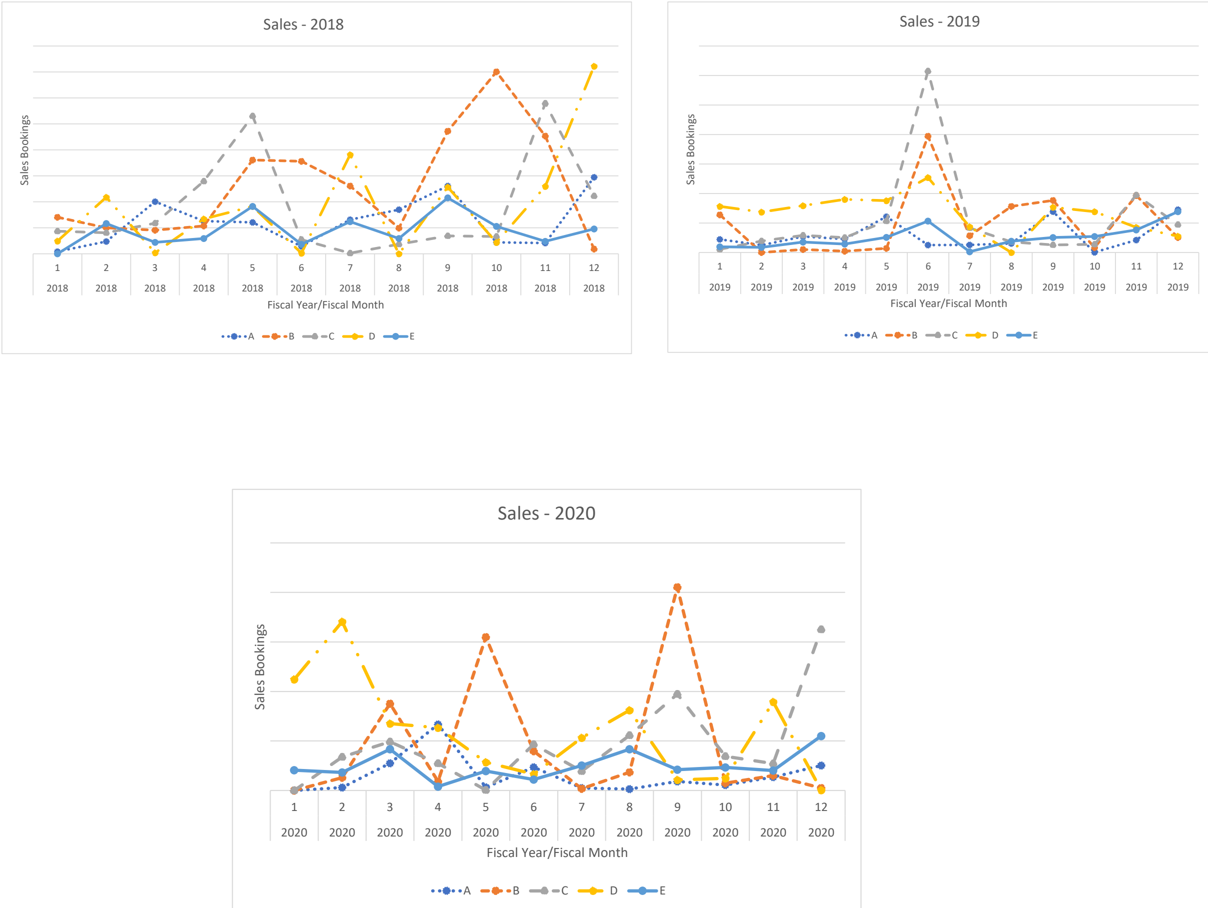

Figure 5.2: Bookings Trend: 2018-2020
Note: Graphs are generated based on the original historical bookings from the year 2018-2020

The historical bookings show that there is seasonality and a trend common in the bookings made by different employees. There is a trend and similarity in the peak and troughs of the bookings of different employees. But on the other hand, the seasonality and the trend are not repeated every year and sometimes the peaks and troughs among the employees are different. This is based on the years of experience of the sales employees. The sales employee who started recently in the company will have a low sales target which will be ramped up based on the experience. Hence the bookings are predicted for each employee to improve the accuracy and reliability of the forecast.

5.3. Quantitative Forecasting Methods

Following the literature review, the forecasting model is built in Excel using the methods mentioned in the section 3.2.1.

5.3.1. Moving Average

This is one of the simple time-series statistical methods to study and forecast the trends in the data. The three-point centered moving average method is used to build the forecasting model in Excel. The historical data from 2018-2020 are fed as input. The output is the average of the bookings made in the last three months from the point of prediction which can be evaluated using the AVERAGE function in Excel. The variance between the normalized actual bookings and forecasts is given as follows:

		Fiscal Year/ Fiscal Month								
		2021	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**
Employee		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
A	Actuals	76	213	1,069	179	226	102	223	276	339
	Forecast	148	155	181	453	487	491	169	183	200
	Variance	**93%**	**-27%**	**-83%**	**153%**	**116%**	**383%**	**-24%**	**-34%**	**-41%**
B	Actuals	134	36	112	197	589	14	25	45	2,435
	Forecast	84	104	65	94	115	299	266	209	28
	Variance	**-38%**	**190%**	**-42%**	**-52%**	**-80%**	**2067%**	**983%**	**362%**	**-99%**
C	Actuals	122	112	430	440	1,577	420	314	-	9
	Forecast	747	673	620	222	327	816	812	770	367
	Variance	**511%**	**502%**	**44%**	**-50%**	**-79%**	**94%**	**159%**	**-**	**4039%**
D	Actuals	158	299	362	793	1,052	571	145	568	367
	Forecast	340	352	153	273	484	735	805	589	428
	Variance	**116%**	**18%**	**-58%**	**-66%**	**-54%**	**29%**	**457%**	**4%**	**17%**
E	Actuals	228	53	319	148	226	475	36	144	708
	Forecast	328	327	277	200	173	231	283	245	218
	Variance	**44%**	**514%**	**-13%**	**36%**	**-23%**	**-51%**	**682%**	**71%**	**-69%**
TOTAL	Actuals	718	712	2,292	1,756	3,668	1,581	742	1,033	3,857
	Forecast	1,647	1,610	1,296	1,241	1,587	2,572	2,335	1,997	1,241
	Variance	**129%**	**126%**	**-43%**	**-29%**	**-57%**	**63%**	**215%**	**93%**	**-68%**
						AVERAGE VARIANCE %			**48%**	

Table 5.1: Moving Average - Actuals vs Forecast
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

The average monthly variance between the actual bookings vs forecast is 48%. The average monthly forecast is not close enough to the actual bookings, and it is not a good method since it can only produce a very short-term rolling forecast of just one month. It requires an input of recent bookings of the last three months. Hence this method is not suitable for making financial planning on a quarter or yearly level.

5.3.2. Exponential Smoothing

The Holt-Winter's Exponential Triple Smoothing method is used to build the sales forecasting model in Excel. The inbuilt FORECAST.ETS function has been used and its measures are defined as follows:

1. Target Date - The target date starts from August 2020 till April 2021. The first three quarters of the fiscal year 2021 are chosen in order to compare the forecast versus the actual bookings.
2. Values - This contains the historical booking values from the fiscal year 2018 till the end of the fiscal year 2020, i.e. from August 2017 till July 2020.
3. Timeline - This contains the period/range of the timeline.

The other optional fields of the FORECAST.ETS function is automatically assumed by the Excel software. In this method, the predictions were again made specific to employees to increase the accuracy of the sales forecasts. The results and the variance of the forecast, when compared to the normalized actual bookings, is mentioned in the graph below:

The average variance between the actual bookings vs forecast is 34% which is better than the moving average method. But the disadvantage of the exponential smoothing method is that it cannot be used to predict sales of the employees who are recently hired due to the absence of historical data.

5.3.3. Regression

Regression is a technique that is used to estimate unknown parameters in a forecasting model using sample data (historical data). Regression has two types: Linear and Multiple regression (Rook, 2020). For this study,

		Fiscal Year/ Fiscal Month								
		2021	2021	2021	2021	2021	2021	2021	2021	2021
Employee		1	2	3	4	5	6	7	8	9
A	Actuals	76	213	1,069	179	226	102	223	276	339
	Forecast	207	- 27	117	257	203	- 31	113	252	198
	Variance	**170%**	**-113%**	**-89%**	**43%**	**-10%**	**-131%**	**-49%**	**-9%**	**-42%**
B	Actuals	134	36	112	197	589	14	25	45	2,435
	Forecast	505	507	509	511	513	515	517	519	521
	Variance	**277%**	**1319%**	**355%**	**159%**	**-13%**	**3628%**	**2001%**	**1047%**	**-79%**
C	Actuals	122	112	430	440	1,577	420	314	-	9
	Forecast	679	561	1,869	898	375	397	471	750	632
	Variance	**456%**	**402%**	**334%**	**104%**	**-76%**	**-5%**	**50%**	**-**	**7025%**
D	Actuals	158	299	362	793	1,052	571	145	568	367
	Forecast	7	11	15	19	23	27	30	34	38
	Variance	**-95%**	**-96%**	**-96%**	**-98%**	**-98%**	**-95%**	**-79%**	**-94%**	**-90%**
E	Actuals	228	53	319	148	226	475	36	144	708
	Forecast	307	311	314	318	321	325	328	332	335
	Variance	**35%**	**484%**	**-1%**	**116%**	**43%**	**-32%**	**809%**	**131%**	**-53%**
TOTAL	Actuals	718	712	2,292	1,756	3,668	1,581	742	1,033	3,857
	Forecast	1,706	1,363	2,823	2,002	1,434	1,232	1,459	1,888	1,725
	Variance	**137%**	**91%**	**23%**	**14%**	**-61%**	**-22%**	**97%**	**83%**	**-55%**
						AVERAGE VARIANCE %			**34%**	

Table 5.2: Exponential Smoothing - Actuals vs Forecast
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

linear regression is used to predict sales using Excel software. The initial step would be to define the variables. Based on the bookings data 5.2, it is seen that there is a seasonality with respect to few months of the fiscal year. Hence to be more precise, the independent variable is assumed as the fiscal month and the bookings as the dependent variable. The historical data from the year 2018-2020 was used to predict the bookings in the year 2021. Hence the measures required to build a regression model are defined as follows:

1. Known X-axis/Independent variable - Fiscal Month
2. Known Y-axis/Dependent variable - Sales bookings from the year 2018-2020 which is the sample data
3. Unknown parameter to be predicted - Sales bookings from the year 2021

The parameters have a traditional interval which is one month. The next step in developing the regression model is to evaluate the statistical use of the model. This can be done in Excel software using an add-in called Analysis ToolPak. The known x-axis and y-axis are fed into the regression tool and the results are generated as follows:

Regression Statistics	
Multiple R	0.15702975
R Square	0.02465834
Adjusted R Square	-0.0048975
Standard Error	210.911043
Observations	35

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	37112.45609	37112.46	0.8343	0.367658219
Residual	33	1467954.448	44483.47		
Total	34	1505066.904			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	171.749738	78.90273254	2.176727	0.03676	11.22092117	332.2785539	11.22092117	332.2785539
Fiscalmonth	9.65785488	10.57353352	0.913399	0.36766	-11.85416082	31.16987057	-11.85416082	31.16987057

Table 5.3: Linear Regression - Model Summary Table
Note: The regression table is generated based on the actual sales bookings values

Interpretation of the Linear Regression Model Summary
The linear regression table provides three different aspects of outputs that can be interpreted in the following way:

1. Regression Statistics
   (a) The value of R - The multiple R represents the correlation between the fiscal month and sales bookings (0.16) (Rook, 2020).
   (b) The value of R Square - The value of R square (0.025) represents that 97.5% of the variation in sales bookings is not explained by the known x-axis (fiscal month). This shows that there is a better independent variable to predict sales (Rook, 2020).
   (c) Adjusted R Square - It says that in case of using a different sample of input, the variance in the bookings forecast would be (-0.005) (Rook, 2020).
2. ANOVA
   The significance of F - This is the most important measure that explains the significance of the regression model. The $p<0.05$ represents that it is highly significant and rejects the null hypothesis but the results 0.37 show that the regression model is not significant. Hence this model does not predict the sales bookings well (Rook, 2020).
3. Coefficients Table
   The t Stat (0.91) and the associated p-value (0.37) of Fiscalmonth are not significantly different from 0. This shows that the independent variable does not make a significant contribution to predicting the dependent variable (Rook, 2020).

This section gives an overview of the chosen time series statistical methods and the forecast variance of each method. The methods were chosen based on the product life cycle stage of the company, its simplicity, and the fact that it can be built using Excel software (since it will be used by financial analysts for forecasts which provides a knowledge boundary and simplicity is a requirement).

Finally, the exponential smoothing method of the time-series statistical methods is the most suitable method for predicting sales bookings but it is not accurate enough. Additionally, it cannot predict the bookings for employees who don't have a history of historical data. Hence, an alternative model using a qualitative method - Sales Department Composite is built in the following section.

5.4. Qualitative Forecasting Methods

This section uses a qualitative forecasting method - Sales Department Composite and then builds a quantitative forecasting model using the estimates provided by the sales department representatives. As mentioned in the section 5.1, the sales made by the employees are recorded as opportunities in Salesforce along with different measures. But in order to develop a quantitative model, some of the numerical estimates are studied. The tableau software is used to visualize the trends and relationships of different variables in sales. From the section 5.3, it is evident that time/fiscal month is not a good variable to predict sales bookings. The other quantitative measures recorded by the sales representative are total amount, PI, MY, Opportunity created date, closed date, briefing date. Other fields such as customer name, account name, theater, area are qualitative and descriptive in nature. The impact of the variables in sales is observed based on the stagename of the opportunity. For historical bookings, an opportunity can be either Closed-Won (Stage 10) or Closed-Lost (stage 0). The unit of observation is different for the qualitative method than the quantitative method. All the filters remain the same except stagename. In quantitative, only closed/successful bookings are chosen to find the relationship between time and sales. But in qualitative both Closed-Won and Closed-Lost bookings are considered. The above-mentioned measures provided by sales representatives are considered as input/independent variable and the stagename is considered as the output/dependent variable. The input variable that is chosen is explained in the following sections.

5.4.1. Choosing the parameters

In order to quantify the model, there should be a correlation and a significant relationship between the input parameters and the stagename of the opportunity - which represents the sales. The following parameters are studied using Tableau:

1. Age - The difference between the opportunity closed date and the created date

2. Total Amount - The total amount of the opportunity/sales booking

Every time a sales representative is getting the first line of contact with a customer, she/he creates an opportunity in Salesforce and provides the measures based on her/his expertise. The above-mentioned parameters are analyzed in detail.

1. **Age**
   This field is not a direct estimate provided by sales employees but is calculated based on the difference in opportunity created and closed date which is sales employees' estimates. The age is grouped based on the count of opportunities in each range. The trend of stagename with respect to the age of the opportunity is tabulated and visualized below. Here, the historical data from the fiscal year 2018-2020 is observed, and the table is attached in the confidential appendix.

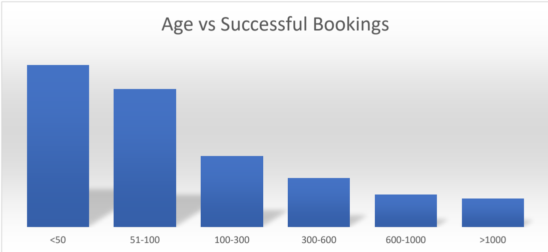

Figure 5.3: Age vs Stagename
Note: The graph is generated based on the actual historical sales bookings values from 2018-2020

This shows that there is a visible trend that indicates a relationship between age and the closed sales represented by stagename of a sales booking. But the relationship and its significance are evaluated using a linear regression technique in Excel. The linear regression table is given below:

Regression Statistics	
Multiple R	0.447775035
R Square	0.200502482
Adjusted R Square	0.200033568
Standard Error	0.435318318
Observations	1707

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	81.02907854	81.02908	427.5894842	6.10296E-85
Residual	1705	323.1009742	0.189502		
Total	1706	404.1300527			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.75691641	0.012571426	60.20927	0	0.732259365	0.781573456	0.732259365	0.781573456
Age	-0.000673333	3.25624E-05	-20.6782	6.10296E-85	-0.000737199	-0.000609466	-0.000737199	-0.000609466

Table 5.4: Regression Table - Age vs Closed Sales Bookings
Note: The regression table is generated based on the actual sales bookings values from 2018-2020

The table can be interpreted the following way:

(a) Regression Statistics

i. The value of R - The multiple R represents the correlation between the age and closed sales bookings (0.44). It has a medium-strength of association. (Rook, 2020).

ii. The value of R Square - The value of R square (0.20) represents that 80.0% of the variation in sales bookings is not explained by the known x-axis (age) (Rook, 2020). This value is better than when the fiscal month was the independent variable.

iii. Adjusted R Square - It says that in case of using a different sample of input, the variance in the bookings forecast would be (0.20) (Rook, 2020). It can be observed that rolling forecasts should be used to have higher accuracy.

(b) ANOVA
The significance of F - This is the most important measure that explains the significance of the regression model. The $p<0.05$ represents that it is highly significant and rejects the null hypothesis and the result shows that the regression model is significant. Hence this variable can be used to predict sales bookings (Rook, 2020).

(c) Coefficients Table
The t Stat and the associated p-value of Age are significantly different from 0. This shows that the independent variable has a significant contribution to predicting dependent variable (Rook, 2020).

Hence, it can be observed that age can be used as an independent variable to predict the dependent variable of sales bookings. But based on the R square value, it is seen that there is still variation that is not explained by age. Hence the total amount is also checked for a relationship with sales below.

2. **Total Amount**
This field is a direct estimate provided by sales employees in Salesforce based on the number and amount of products that the customer is willing to purchase. The age is grouped based on the count of opportunities in each range. The trend of closed bookings with respect to the total amount of the opportunity is tabulated and visualized below. Here, the historical data from the fiscal year 2018-2020 is observed, and the table is attached in the confidential appendix.

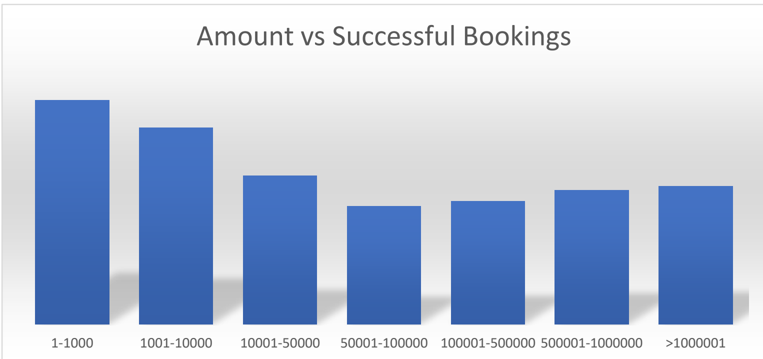

Figure 5.4: Amount vs Stagename
Note: The graph is generated based on the actual historical sales bookings values from 2018-2020

This doesn't show an evident trend as compared to age versus closed bookings. But there's still a decreasing trend with closed bookings with an increase in the total amount. Hence it is required to check if there is a statistical significance using a linear regression model. The output of the linear regression model is given below:

The table can be interpreted the following way:

(a) Regression Statistics

i. The value of R - The multiple R represents the correlation between the amount and closed sales bookings (0.103). It has a low strength of association. (Rook, 2020).

ii. The value of R Square - The value of R square (0.20) represents that 98.9% of the variation in sales bookings is not explained by the known x-axis (age) (Rook, 2020). This shows that amount alone cannot be used to predict bookings.

Regression Statistics	
Multiple R	0.103502215
R Square	0.010712708
Adjusted R Square	0.010132481
Standard Error	0.484238814
Observations	1707

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	4.329327418	4.329327	18.46295612	0.000018
Residual	1705	399.8007253	0.234487		
Total	1706	404.1300527			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.639140749	0.012985939	49.21791	0	0.613670696	0.664610802	0.613670696	0.664610802
Amount	-2.56971E-07	5.98045E-08	-4.29685	0.000018	-3.74269E-07	-1.39673E-07	-3.74269E-07	-1.39673E-07

Table 5.5: Regression Table - Amount vs Closed Sales Bookings
Note: The regression table is generated based on the actual sales bookings values from 2018-2020

iii. Adjusted R Square - It says that in case of using a different sample of input, the variance in the bookings forecast would be (0.01) (Rook, 2020). It shows that using a different sample of input will not produce much variance to the result.

(b) ANOVA
The significance of F - This is the most important measure that explains the significance of the regression model. The $p<0.05$ represents that it is highly significant and rejects the null hypothesis and the result shows that the regression model is significant. Hence this variable can be used to predict sales bookings (Rook, 2020).

(c) Coefficients Table
The t Stat and the associated p-value of Age are significantly different from 0. This shows that the independent variable has a significant contribution to predicting dependent variable (Rook, 2020).

It can be observed that there is a significant relationship between the amount and the sales bookings. But it is not as strong as age versus sales bookings. Hence a multiple regression was carried out to check if the amount was a moderator variable that moderates the relationship between age (independent variable) and the closed bookings (dependent variable). The results and interpretation of the multiple regression are given as follows:

The table shows only a slight improvement in the r-value of 0.449 when compared to regression having alone 0.447. But the significance has increased a lot when compared to use age or amount alone to predict sales. It can be concluded that amount moderates the relationship between age and sales to some extent and hence it should be included in the quantified model of the sales forecast. The relationship of the variables that will be used in the forecasting model is shown below:

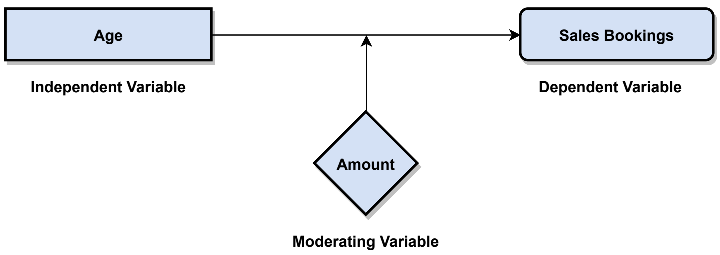

Figure 5.5: Relationship between variables (Sekaran and Bougie, 2016)

Regression Statistics	
Multiple R	0.449825799
R Square	0.202343249
Adjusted R Square	0.201407032
Standard Error	0.434944458
Observations	1707

ANOVA

	df	SS	MS	F	Significance F
Regression	2	81.77298802	40.88649	216.1286146	2.22469E-84
Residual	1704	322.3570647	0.189177		
Total	1706	404.1300527			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.765101401	0.013221424	57.86831	0	0.739169468	0.791033335	0.739169468	0.791033335
Age	-0.000664461	3.28406E-05	-20.2329	9.42057E-82	-0.000728873	-0.000600049	-0.000728873	-0.000600049
Amount	-1.07523E-07	5.4222E-08	-1.98302	0.047525954	-2.13872E-07	-1.17439E-09	-2.13872E-07	-1.17439E-09

Table 5.6: Multiple Regression Table - Amount vs Age vs Closed Sales Bookings
Note: The multiple regression table is generated based on the actual sales bookings values from 2018-2020

The combined effect of age and amount will be used to predict sales bookings. The quantified sales forecasting model is explained in the following section.

5.5. Sales Forecasting Model - Combined forecasting method

This section explains the logic behind the sales forecasting model built using sales employees' estimates and discusses the results of the forecast in comparison with actual sales. Though the inputs are the estimates given by the sales employees, the variables are chosen and the relationship between them is explained using time series statistical methods. Hence, this is referred to ask the combined forecasting method.

The effect of age and amount on sales is measured by a probability function. The historical bookings are grouped in the predefined groups of age and amount. The data is then analyzed using Tableau software to identify the probability measure. The probability is obtained by the percentage of actual bookings closed in the previous years from 2018-2020. To provide more accuracy, the probability measure is defined for each employee. As mentioned previously, the sales bookings made by an employee depend on the years of experience. Hence it is also included to increase the reliability and accuracy of the probability measure. The average percentage of closed bookings made by employees based on age and amount is used as a probability to predict future sales. But there are cases when an employee has never made a booking in a particular combination of age and amount. For example, employee A has never made a historical booking that falls into the age group of <50 and the amount group of 1-1000. In those cases, the next best-case scenario is chosen. The correlation coefficient of both age and amount with sales bookings is tabulated below.

	Age	Amount	Stage
Age	1		
Amount	0.136225	1	
Stage	-0.44778	-0.1035	1

Table 5.7: Age vs Amount Correlation (Sekaran and Bougie, 2016)
Note: The correlation table is generated based on the actual sales bookings values from 2018-2020

It shows that age has medium strength of correlation (-0.44) and the amount has a correlation of (-0.11) with sales bookings. Here age has more impact on sales bookings which can be explained by its correlation coefficient being closer to -1. Hence age has priority over the amount in the probability function. The input, probability condition, and the output of the model is discussed below:

1. Input - All the opportunities of the fiscal year 2021 (that includes all closed-won, closed-lost, open opportunities related to Middle East sales employees)
2. Probability condition - This is the probability at which an opportunity will be closed. The probability is derived based on the historical data from 2018-2020.
3. Output - This includes the sales forecast prediction of the model.

Finally, the condition to derive at the probability function is explained below in the form of a flowchart below:

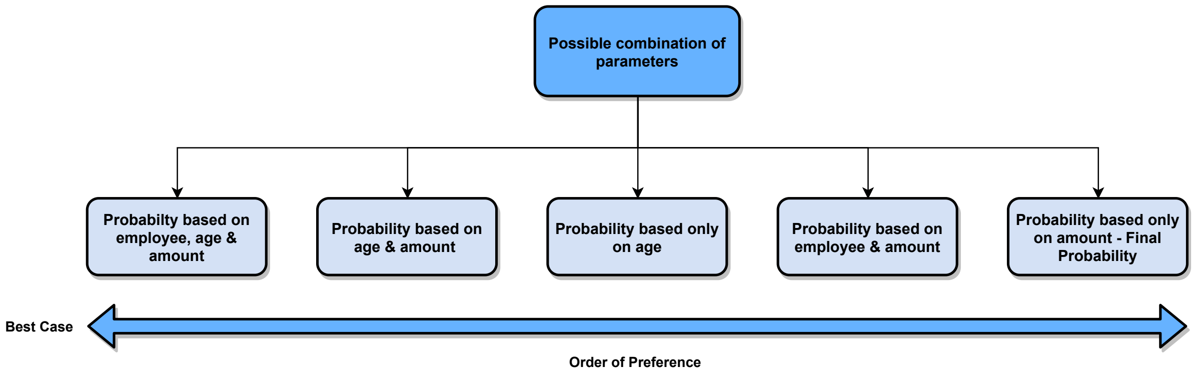

Figure 5.6: Probability Condition Flowchart

Finally, based on the probability function a formula has been formulated in Excel to predict sales bookings. In this model, it is assumed that the booking will be closed at the date estimated by the employee. Hence based on the probability and the estimated close date, the sales are predicted for the first three quarters of the fiscal year 2021. Then the sales forecast is compared with the actual sales data made in the first three quarters of 2021. The result of the forecasting model is tabulated as follows:

The average variance while using the combined forecasting methods is similar to exponential smoothing but this method can predict the bookings in spite of the absence of availability of historical data. In the absence of historical data for employees, the model can still use other cases as mentioned in the 5.6. The factor driving the highlighted variance is analyzed and has been explained in detail below.

The variance is mainly driven by sales bookings which fall into the age category of <50 and the total amount category of 100,001 - 500,000. Based on the probability preference order 5.6, it takes the probability of the best-case scenario (Probability combination of employee, age & amount). The predicted probability for this opportunity to be closed is 56%, but in the real case, this booking was lost.

Though the chosen input parameters and the probability preference order provided close accuracy in most cases, it had a huge variance in this particular case. Hence this opportunity was studied in detail in order to point out the factor that will predict sales with more accuracy. The data was filtered to choose the opportunities that were in the same age and amount category to identify and validate the main differences. On analyzing and comparing this opportunity with other successful opportunities, there was an evident difference in the sales pipeline stages.

The pipeline in the Salesforce software provides a detailed summary of the available opportunities, the timeline, sales funnel/stages, and the revenue the opportunity will generate. One of the important characteristics of the opportunity is the sales funnel which represents the journey of the opportunity since the moment it was created. The different stages of the sales funnel should be used and transformed into two purposes:

		Fiscal Year/ Fiscal Month								
		2021	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**
Employee		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
A	Actuals	76	213	1,069	179	226	102	223	276	339
	Forecast	86	451	1,004	259	175	114	82	125	229
	Variance	**13%**	**112%**	**-6%**	**45%**	**-22%**	**12%**	**-63%**	**-55%**	**-33%**
B	Actuals	134	36	112	197	589	14	25	45	2,435
	Forecast	121	41	602	28	298	309	162	253	2,178
	Variance	**-10%**	**15%**	**439%**	**-86%**	**-49%**	**2136%**	**559%**	**459%**	**-11%**
C	Actuals	122	112	430	440	1,577	420	314	-	9
	Forecast	1,383	695	771	324	337	778	228	12	1,561
	Variance	**1031%**	**521%**	**79%**	**-26%**	**-79%**	**85%**	**-27%**	**-**	**17502%**
D	Actuals	158	299	362	793	1,052	571	145	568	367
	Forecast	130	482	267	590	880	647	91	410	302
	Variance	**-18%**	**61%**	**-26%**	**-26%**	**-16%**	**13%**	**-37%**	**-28%**	**-18%**
E	Actuals	228	53	319	148	226	475	36	144	708
	Forecast	125	59	159	376	209	84	163	172	668
	Variance	**-45%**	**10%**	**-50%**	**155%**	**-8%**	**-82%**	**351%**	**19%**	**-6%**
TOTAL	Actuals	718	712	2,292	1,756	3,668	1,581	742	1,033	3,857
	Forecast	1,844	1,728	2,804	1,577	1,900	1,932	725	972	4,938
	Variance	**157%**	**143%**	**22%**	**-10%**	**-48%**	**22%**	**-2%**	**-6%**	**28%**
						AVERAGE VARIANCE %			**34%**	

Table 5.8: Combined method forecasting model - Actuals vs Forecast
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

1. To explain the customer buying pipeline process
2. To understand and align the efforts exhibited by sales and marketing in acquiring the customers (Patterson, 2007).

The different stages of the sales funnel are listed below (Colicev et al., 2019):

1. Awareness - This mentions the level of customers' awareness and perception of the company and its products.
2. Consideration - This refers to the interest of the customer to make the purchase.
3. Purchase intent - This refers to the confidence/commitment made by the customer to buy from the company.
4. Satisfaction - This refers to the satisfaction of the customer that comes from the product and its purchasing journey.

The above-mentioned methods are covered in the literature but the organization has specific sales pipeline stages based on their characteristics. The sales funnel stages specific to Palo Alto Networks is shown below:

The stage 1 & 2 are associated with the awareness stage, stage 3 & 4 associated with consideration, and stage 5 with the purchase intent stage.

The historical bookings were observed against the sales funnel stages. In particular, the opportunities that belong to the total amount group greater than 50,000 and the age group less than 50 were chosen. One of the opportunities was moved to stage 3 - Solution before it was Closed - Won. Another opportunity was in stage 4 - Negotiate before the final purchase. This shows that successful opportunities cross stage 3 of the sales funnel before it is closed by the sales representative. Finally, the opportunity that caused a huge variance of 17502% was observed. It was seen that the opportunity never crossed stage 1 - Qualify and it was Closed-Lost. This shows that sales funnel pipeline stages being an important indicator to predict the success of a sales booking. In this thesis, the current SFM framework is modified and quantified to predict the sales forecasting performance. But the results show that the sales pipeline stages and their characteristics should

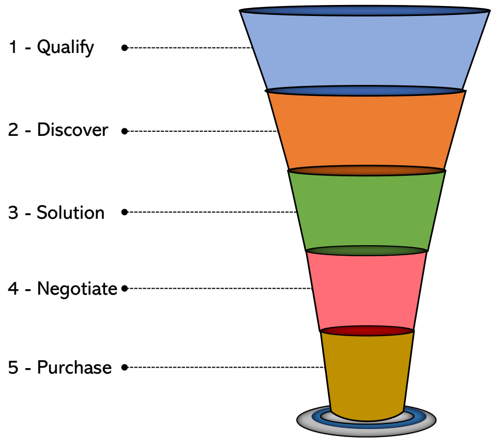

Figure 5.7: Sales Funnel Stages

be included as a factor in the theory-based SFM framework. The credibility of the sales pipeline characteristics depends on effective collaboration between Sales, Marketing, and Finance teams in providing accurate estimates (Patterson, 2007). The effective use of CRM software to explain the sales pipeline stages also influences the sales forecasting performance. Finally, the sales pipeline stages show a strong connection with the components of sales forecasting capabilities of the SFM framework (Collaboration, Information Logistics) as mentioned in the section 3.1.1.

5.6. Summary

This chapter starts with the utilization of the research design mentioned in (Sekaran and Bougie, 2016) as a framework to explain the data collection method. The research design helps to define the scope of the thesis by explaining the unit of observation and the systematic steps to collect the data as mentioned in the figure 5.1.

And based on the results of the literature review 3, both quantitative and qualitative forecasting methods are analyzed to determine the appropriate forecasting technique. The summary of the analysis and results of the forecasting methods is given below in the figure 5.9:

The result of the chapter provides the answer for the second research question as mentioned in the section 1.3. It mentions that the combined qualitative and quantitative forecasting method is the most appropriate method to predict sales under the context of Palo Alto Networks. It is essential to have a well-integrated network of information systems to build the chosen forecasting model as it utilizes Salesforce, Google Cloud Platform (GCP), Tableau, and Excel along with knowledge transfer between cross-functional teams. Thus, the data collection, analysis, and simulation model validate the importance of the sales forecasting climate, information logistics, and cross-communication elements of the modified SFM framework. Finally, this chapter also identifies an important knowledge gap of the existing sales forecasting management literature - the absence of the inclusion of sales pipeline stages in the sales forecasting framework. The result of this chapter shows the variance in the current sales forecasting model can be reduced to a great extent by including the impact of sales pipeline stages in the simulation model. This exhibits that the sales forecasting performance and accuracy can be improved by including the sales pipeline characteristics in the current sales forecasting management literature.

The sales forecasting method will be combined with sales forecasting climate components (sales compensation structure and UAE Labor Law) to quantify the effect of sales forecasting performance on business outcomes. This will be explained in the following chapter.

Forecasting Method	Input	Output	Time Horizon	Variance (%)	Inference	Recommended
Moving Average	Recent historical bookings (of the past 3 months)	Sales bookings	Short-term rolling forecasts	48%	This method has the least accuracy. The method cannot predict bookings for new employees and it need the recent historical bookings. Hence it cannot be used for quarterly/yearly financial planing purposes.	No
Exponential Smoothing	Historical bookings from 2018-2020	Sales bookings	Medium-term rolling foreasts	34%	This method has a good accuracy. This method still cannot be used since it cannot predict sales for new employees.	No
Regression	Historical bookings from 2018-2020	Sales bookings	Medium-term rolling foreasts	NA	The statistical method is proved to be insignificant. This shows that there is not a significant seasonality. In other terms, the relationship between time and sales bookings is not significant enough.	No
Combined Forecasting method	Historical bookings from 2018-2020	Sales bookings	Medium-term rolling foreasts	34%	This method has a good accuracy. This is a good method to predict sales bookings. It can be used to predict sales bookings of new employees and can be used for financial planning. Further, this method has room for improvements and good directions for future research to increase the accuracy in the prediction.	**Yes**

Table 5.9: Summary of forecasting method results (Sekaran and Bougie, 2016)(Rook, 2020)

6

Performance Outcomes

This chapter measures the effect of sales forecasting performance in the final business outcome - End of Service Benefits (EOSB). The forecasting method is chosen based on the results of the chapter 5. The sales forecasts are used to calculate the commissions of the employees based on the compensation structure explained in the chapter 4.3. Finally, the commissions' forecast is used to calculate the End of Service Benefits for the employees. The results of this chapter provide the answer for sub-question 3.

6.1. Sales Commissions Calculation

The Sales Compensation structure is defined by the financial team of the headquarters and it is maintained by the sales planning team of Europe, the Middle-East, and Africa (EMEA). In this thesis, the sales compensation structure is assumed to be given. The inputs and output of the compensation structure are explained below:

1. **Input:**
   (a) Quota - The quota is the target that is set for each employee. The employee has a predefined quarterly target. The quota is set based on the product type, years of experience of the employee, etc.
   (b) On-Target Incentive (OTI) - This is the monthly commission entitled to the employee on achieving 100% of the target.
2. **Output:**
   (a) Base Compensation Rate (BCR) - As mentioned in the section 4.3, BCR is defined as OTI/Quota.
   (b) Multi-year (MY) - As mentioned in 4.3, MY is given by x*BCR. (the rate is mentioned as x due to confidentiality reasons)

For this thesis, the Strata bookings are studied since they contribute to nearly 96% of the total bookings. The employees have separate quotas/targets for Strata and Speedboat bookings. Hence the BCR and MY of strata quota alone are considered. The compensation structure along with the calculation of BCR and MY is included in the confidential appendix.

The outputs of the sales compensation plan (BCR & MY) are used to calculate the commissions of each employee. The inputs and outputs of the commission model are given as follows:

1. **Input:**
   (a) PI Bookings - It is part of the total amount of the opportunity/booking. It includes the revenue generated by the hardware product and the initial yearly revenue generated from subscriptions and support.
   (b) MY Bookings - It is also a part of the total amount which is the revenue that will be incurred by the company in the future fiscal years as mentioned in 4.3.
   (c) BCR - The output from the Compensation structure is given as the input for the commission model.

(d) MY - The output from the Compensation structure is given as the input for the commission model.

2. **Output:**

(a) Commission - The monthly commissions of all the sales employee is calculated as a result of this model.

The total commission is given by:
Total commissions = PI commission + MY commission, where
PI = BCR*PI bookings
MY = MY* MY Bookings

The actual commissions are calculated using the PI and MY of the actual sales opportunities/bookings. The actual commissions are calculated for the fiscal year 2021 for all the sales employees. They are then compared with the commissions calculated from bookings forecast as mentioned in 5.8. Before comparing the actual versus forecast commissions, we know from above that the variables PI and MY are inputs for the commission model. Hence it should be added to the combined forecasting method 5. The PI and MY are provided by the sales employees in the Salesforce software every time a new opportunity is created. The weights of the PI and MY with respect to the total amount is calculated based on sales department estimates. Finally, the PI and MY variables are predicted based on the calculated PI and MY weights. The commissions are calculated using actual bookings and the predicted sales bookings and tabulated for comparison as given below:

		Fiscal Year/ Fiscal Month								
		2021	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**	**2021**
Employee		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
A	Actuals	9	24	125	22	26	12	26	33	39
	Forecast	10	51	118	21	13	30	10	15	26
	Variance	**12%**	**111%**	**-6%**	**-6%**	**-48%**	**160%**	**-63%**	**-55%**	**-33%**
B	Actuals	15	4	14	26	63	2	3	6	244
	Forecast	13	5	66	39	32	4	21	29	218
	Variance	**-10%**	**14%**	**357%**	**51%**	**-48%**	**104%**	**548%**	**385%**	**-10%**
C	Actuals	14	14	42	49	210	46	38	-	1
	Forecast	141	76	80	38	102	36	27	1	172
	Variance	**945%**	**456%**	**90%**	**-23%**	**-51%**	**-22%**	**-27%**	**-**	**19194%**
D	Actuals	14	26	34	68	95	56	13	50	35
	Forecast	11	41	26	75	58	55	8	37	29
	Variance	**-19%**	**59%**	**-25%**	**12%**	**-38%**	**-2%**	**-37%**	**-26%**	**-16%**
E	Actuals	34	8	45	21	32	67	6	19	97
	Forecast	19	8	21	32	12	54	27	26	96
	Variance	**-45%**	**8%**	**-52%**	**50%**	**-62%**	**-19%**	**347%**	**35%**	**0%**
F	Actuals	1	38	36	8	32	56	37	65	42
	Forecast	3	54	41	22	14	54	16	44	160
	Variance	**149%**	**39%**	**14%**	**178%**	**-56%**	**-4%**	**-58%**	**-33%**	**281%**
G	Actuals	11	19	5	21	5	114	0	29	4
	Forecast	22	34	2	28	8	58	5	29	4
	Variance	**101%**	**80%**	**-48%**	**34%**	**38%**	**-49%**	**2829%**	**-1%**	**4%**
H	Actuals	15	16	40	32	15	18	1	4	94
	Forecast	13	12	37	5	14	8	20	2	48
	Variance	**-17%**	**-25%**	**-9%**	**-84%**	**-9%**	**-58%**	**3167%**	**-38%**	**-49%**
I	Actuals	-	1	38	13	55	27	15	3	-
	Forecast	-	0	35	78	30	13	6	45	-
	Variance	**-**	**-21%**	**-6%**	**483%**	**-46%**	**-52%**	**-58%**	**1275%**	**-**
TOTAL	Actuals	112	150	380	259	534	398	138	210	555
	Forecast	232	282	426	337	284	312	140	228	754
	Variance	**107%**	**88%**	**12%**	**30%**	**-47%**	**-22%**	**1%**	**9%**	**36%**
						AVERAGE VARIANCE %			**24%**	

Table 6.1: Commissions - Actuals vs Forecast
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

It can be observed that the highlighted variance is caused due to the high variance of sales bookings as mentioned in the result of the combined forecasting method 5.8. The overall average for all the employees for the first three quarters is 24%.

Currently, the EMEA (Europe, Middle-East, and Africa) Sales finance team assumes that the employees achieve their target every month due to the unavailability of the sales bookings forecast. Hence OTI (On-Target Incentive) is assumed as the commission received by the employees in order to predict the EOSB (End of Service Benefits). The variance of the actual commissions with respect to OTI is tabulated as follows:

		Fiscal Year/ Fiscal Month								
		2021	2021	2021	2021	2021	2021	2021	2021	2021
Employee		1	2	3	4	5	6	7	8	9
A	Actuals	9	24	125	22	26	12	26	33	39
	OTI	11	11	11	11	11	11	11	11	11
	Variance	**20%**	**-56%**	**-91%**	**-52%**	**-59%**	**-7%**	**-59%**	**-67%**	**-72%**
B	Actuals	15	4	14	26	63	2	3	6	244
	OTI	13	13	13	13	13	13	13	13	13
	Variance	**-14%**	**185%**	**-12%**	**-51%**	**-80%**	**605%**	**296%**	**115%**	**-95%**
C	Actuals	14	14	42	49	210	46	38	-	1
	OTI	12	12	12	12	12	12	12	12	12
	Variance	**-14%**	**-15%**	**-72%**	**-76%**	**-94%**	**-75%**	**-69%**	**-**	**1201%**
D	Actuals	14	26	34	68	95	56	13	50	35
	OTI	12	12	12	12	12	12	12	12	12
	Variance	**-17%**	**-55%**	**-66%**	**-83%**	**-88%**	**-79%**	**-8%**	**-77%**	**-67%**
E	Actuals	34	8	45	21	32	67	6	19	97
	OTI	12	12	12	12	12	12	12	12	12
	Variance	**-63%**	**60%**	**-72%**	**-41%**	**-62%**	**-81%**	**106%**	**-36%**	**-87%**
F	Actuals	1	38	36	8	32	56	37	65	42
	OTI	10	10	10	10	10	10	10	10	10
	Variance	**718%**	**-75%**	**-74%**	**23%**	**-71%**	**-83%**	**-74%**	**-85%**	**-77%**
G	Actuals	11	19	5	21	5	114	0	29	4
	OTI	10	10	10	10	10	10	10	10	10
	Variance	**-8%**	**-47%**	**123%**	**-51%**	**84%**	**-91%**	**5444%**	**-66%**	**187%**
H	Actuals	15	16	40	32	15	18	1	4	94
	OTI	11	11	11	11	11	11	11	11	11
	Variance	**-28%**	**-31%**	**-72%**	**-65%**	**-27%**	**-39%**	**1688%**	**203%**	**-88%**
I	Actuals	-	1	38	13	55	27	15	3	-
	OTI	11	11	11	11	11	11	11	11	11
	Variance	**-**	**1925%**	**-71%**	**-17%**	**-80%**	**-59%**	**-24%**	**238%**	**-**
TOTAL	Actuals	112	150	380	259	534	398	138	210	555
	OTI	101	101	101	101	101	101	101	101	101
	Variance	**-10%**	**-33%**	**-73%**	**-61%**	**-81%**	**-75%**	**-27%**	**-52%**	**-82%**
						AVERAGE VARIANCE %			**-55%**	

Table 6.2: Commissions - Actuals vs OTI
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

It can be observed that the average variance is -55%. This shows that the commissions that are predicted as a result of the sales forecasting method produce a more accurate result. Additionally, the variance of actual commissions versus forecast is positive whereas it's negative for commissions versus OTI. In this case, it is better to have 24% more investment as a placeholder during financial planning rather than being short of -55%. Moreover, the graph below suggests that the model predicts the seasonality and the trends of the commissions' forecast close to the actual commissions received by the employees.

Hence the effect of sales forecasting performance on employees' commissions is quantified and it proves that the combined sales forecasting model produces closer predictions with good accuracy.

6.2. End of Service Benefits Calculation

In this study, the final business outcome measured and analyzed is the End of Service Benefits. The aim of the thesis is to quantify and test the SFM framework in the organizational setting of a high-tech industry such as Palo Alto Networks. This part explains the effect of sales forecasting performance in predicting the End of Service Benefits for UAE employees. As explained in the section 4.4, the final EOSB model is built using the following inputs:

1. Years of Service - This represents the years of service of the employee at the company. The difference between the current fiscal month-end date and the hiring date gives the employees' years of service. The month at which the EOSB is predicted is denoted as the current month-end date.

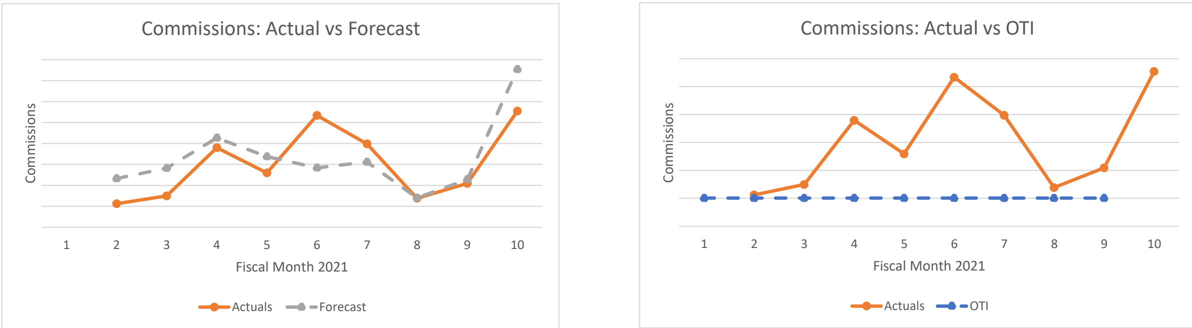

Figure 6.1: Commissions - Actuals vs Forecast vs OTI
Note: The graph contains normalized actuals & forecast sales bookings values for confidentiality reasons

2. Base Salary - This is one of the variables that is required to calculate the EOSB. The base salary of the employee is assumed to be fixed and the details are collected from the payroll team.

3. Commissions - As mentioned in the section 4.4, the EOSB depends on both Base salary and commissions. The EOSB depends on the commissions received by the employee for the last six months from the current fiscal month-end date. For example, to predict the EOSB at the end of July, the commissions received by the employees from January till June are required.

Of all the inputs required for EOSB, commissions of the employees are the only variable and others are fixed components. The main aim of the sales forecasting method is to predict the commissions. Assume that the EOSB at the end of January is to be calculated. The calculations are explained below in detail (Laws, 2001):
Total Commissions = Commissions (August + September + October + November + December + January)
Average Commissions = Total commissions/6
Total rate = Base Salary + Average commissions
Daily rate = (Total rate * 12)/365
EOSB entitlement (till date) = Years of service * Daily rate * 30

Based on the years of service, the employee is entitled to a specific EOSB. As mentioned in the table 4.4, the final EOSB payout is calculated:

1. If the employee has worked less than a year, he is not entitled to any gratuity pay.

2. If the employee has worked between 1 to 3 years, he is entitled to 33% (1/3) of the EOSB entitlement.

3. If the employee has worked between 3 to 5 years, he is entitled to 67% (2/3) of the EOSB entitlement.

4. If the employee has worked more than 5 years, he is entitled to 100% of the EOSB entitlement.

Based on the above calculations the final EOSB model is built. The actual EOSB (built using the actual commissions) is compared against the EOSB forecasts (built using the predicted commissions) and EOSB built using OTI. The EOSB is predicted as of 31/01/2021 (January end) and the results are tabulated below:

The results of the EOSB model show a very good accuracy (-2%) when commissions forecasts were used rather than the On-Target Incentive (-57%). Finally, the Sales Finance team will have to accrue for the End of Service Benefits. This proves that the quantified model of the SFM framework produces a positive effect on one of the important operational business expenditures - EOSB. Additionally, by predicting the commissions of the sales employees, the model can also be extended to predict their earnings in the future.

	End of Service Benefits (As of 31/01/2021)		
Employee	**Actuals**	**Forecast**	**OTI**
A	265	273	114
B	19	24	15
C	126	115	37
D	97	89	37
E	67	61	39
F	24	23	10
G	10	9	5
H	8	7	6
I	-	-	-
Total EOSB	**616**	**601**	**265**
Variance		**-2%**	**-57%**

Table 6.3: Effect of sales forecasting on EOSB
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

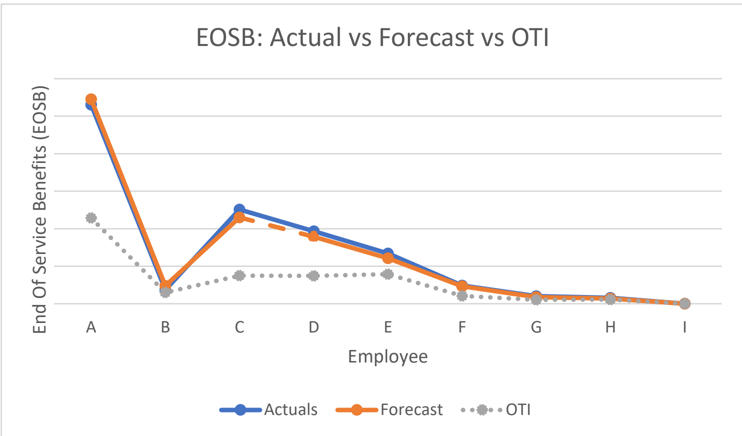

Figure 6.2: EOSB: Actual vs Forecast vs OTI
Note: The graph contains normalized actuals & forecast sales bookings values for confidentiality reasons

6.3. Role of Top Management in Sales Forecasting

The thesis aims to explain the feedback loop of the SFM framework - the role of top-level management on sales forecasting performance as mentioned in chapter 4. The level of commitment of top-level management in the sales forecasting process has a significant effect on its performance (Moon et al., 2003). The top management involvement in the forecasting includes the approval of the forecasts and investigation to a lesser extent. The participation of executives in the investigation of forecasts increased the number of methods used for the forecasts and its objectivity which in turn increased the forecast accuracy (West, 1994). The paper (Durand, 2003) explains that having a high self-perception of a firm's performance has a negative effect on forecast accuracy while an organization's increased support of employee education has a positive impact on the accuracy. These findings are critical and top-level executives must be aware of the organizational factors that affect the forecast accuracy. It is evident that top-level management's involvement has a positive impact on forecast accuracy. Hence it becomes important to identify how the top-level executives can stimulate and improve forecasting performance. As mentioned in the chapter 4, there is a high demand from top-level executives for higher forecast accuracy. Based on the results of the final simulation model, it is important to explain up to which extent the top-level management can improve the sales forecasting performance. Based on the modified SFM framework and the quantified simulation model, the following observations and key takeaways are provided for top-level executives:

1. Collaboration - For this study, collaboration is a crucial element. Collaboration is one of the key values of Palo Alto Networks (Palo Alto Networks, 2021) which has paved the way to develop the sales forecasting model. Specifically for this thesis, there was ample between different departments such as,
   (a) Sales Planning - To develop the compensation structure model
   (b) Sales Operations - To understand the information process such as understanding the logistics of CRM software, Google Cloud Platform, and Tableau. The collaboration was mainly useful for data collection.
   (c) Business Analysis team - To understand the different sales pipeline stages and the information provided by the sales employees. This collaboration was used in data collection & analysis but specifically to explain the directions for future research. This shows the importance of collaboration in high-tech industries, and it's the responsibility of top-level management to ensure an organizational climate that promotes collaboration and knowledge transfer.
2. Credibility of Sales Department Composite - Based on the results of the chapter 5, it is observed that the appropriate method to predict sales is the sales department composite. This method is highly dependent on the accuracy of the estimates provided by the sales employees. Hence, top-level executives should communicate the importance of the accuracy of sales department estimates. Further, promotions and awards programs can be developed to appreciate the employees who maintain accuracy in their estimates.
3. Effective use of Information Logistics - It is evident that effective use of information logistics and mastery with different software applications are essential to improve sales forecasting performance. The top-level executives should promote efficient and cohesive data management practices that aids in revenue management and better forecasting accuracy (Boyle, 2004). Additionally, the employees should be encouraged to indulge in continuous learning practices. For example, employees can be provided with free access to online courses to improve their technical skills and master different software applications.

These are some of the key insights that demand more importance from top-level executives. Through this study, there is ample evidence that sales forecasting performance can be improved when top-level management intervenes to improve the above-mentioned organizational climate characteristics.

6.4. Summary

The results of this chapter show that the quantified SFM framework and the combined forecasting technique is an efficient method to forecast the End of Service Benefits with high accuracy (Variance - -2%). The results of this chapter are tabulated as follows:

	Variance %	
	Forecast	OTI
Commissions	24%	-55%
End of Service Benefits (EOSB)	-2%	-57%

Table 6.4: Impact of Sales forecasting performance on Commissions and EOSB
Note: The table contains normalized actuals & forecast sales bookings values for confidentiality reasons

Further, the key insights gathered throughout this study have been gathered to provide prime suggestions for top-level management to improve sales forecasting performance. Therefore, the feedback loop of the SFM framework has been explained in brief. Finally, the thesis has explained the effect of sales forecasts on improving business performance, tested the validity of the SFM framework, and found the academic gap in the current framework and the forecasting methods.

7
Conclusion

This chapter offers a conclusion to the research question of this thesis followed by a discussion of the scope of the thesis, limitations, and directions for future research.

7.1. Answers to research questions

The main research question is answered by combining the theory and quantitative results obtained from the three sub-research questions. The most important contribution of this study is utilizing a theory-based sales forecasting management, choosing and building a sales forecasting model using the framework, studying its quantitative results on business performance. The chapter 5 develops a novel forecasting method to validate the framework and thereby provide ways for the organization to improve its sales forecasting managerial practices. The originality of the thesis lies in the research methodology of developing the model where the different parameters (opportunity created & closed date, total amount) provided by the sales department are validated and quantified using quantitative concepts namely the regression and correlation. The thesis has also effectively validated different aspects of the modified SFM framework which can be replicated by the high-tech organization to improve the sales forecasting performance. The research question is given as:

How can a high-tech organization (Palo Alto Networks) improve its business performance using sales forecasts?

The main aim of the thesis is to provide a detailed explanation of ways to improve the sales forecasting process in order to improve the business performance outcome. In this study, the business performance that has been considered is the End of Service Benefits (EOSB). As mentioned in chapter 1, this is the termination/gratuity payment the employee receives on leaving the company. This is an important operational expenditure for the company which requires an efficient forecasting process. For a publicly listed company, it is crucial to building efficient financial forecasts/plans since inaccuracies in forecast affect the Earnings Per Share (EPS) and stock value. In order to provide directions for improving the sales forecasting process, a framework called Sales Forecasting Management (SFM) as given in the figure 3.1 is considered from the literature (Davis and Mentzer, 2007) which is a theory-based framework developed to explore different organizational factors that have an impact on sales forecasting management. This framework has been modified according to the specific business performance (EOSB) and the organizational setting of a high-tech industry as mentioned in the figure 4.1 such as Palo Alto Networks. The redefined SFM framework (Fig: 4.1) as mentioned in chapter 4 is quantified and validated under the empirical setting of Palo Alto Networks. The organizational factors as mentioned in the SFM framework are tested across this study and are also used to choose an appropriate forecasting method. A quantified sales forecasting model is built which is further extended to forecast the business outcome, EOSB. The influence of the sales forecasting climate and capability factors play an important role in choosing the forecasting technique and also has a direct impact on the forecasting process. Hence, the main research question is answered by studying the organizational characteristics, developing a quantified SFM framework, validating the results, and measuring its effect on the business performance helps an organization to improve its forecasting accuracy of operational expenditure with the use of sales forecasts. The following sub-research questions were formulated to answer the main research question.

1. **What are the characteristics of a high-tech company (Palo Alto Networks) that influence sales forecasting management?**

   The sales forecasting performance is highly dependent on the characteristics of the organization. Hence in the article (Davis and Mentzer, 2007), the authors have explained the organizational factors into three different components - Sales Forecasting Climate, Sales Forecasting Capability, and Performance Outcome as given in section 3.1.1. Every component constitutes different elements and the framework is modified as given in 4.1 with specific elements chosen for this study. The modified Sales Forecasting framework is explained below:

   (a) Sales Forecasting Climate
   The sales forecasting climate is referred to the components and factors that affect the sales forecasting practices and decision-making. In this thesis, the climate is considered to be the organizational characteristics that are relevant to top-level management and the sales employees which have a direct influence on the sales forecasting procedure and performance (Davis and Mentzer, 2007). The organizational characteristics that influence the sales forecasting process and the End of Service Benefits are the compensation structure, UAE labor law, and product life cycle stage of the company. These components of the modified SFM framework are compared in the section 4.5 with the original SFM framework to justify and increase the applicability of the framework for this thesis study. The compensation structure is an internal characteristic that defines the variables that are required to forecast the commissions earned by the employees. The UAE labor law is an external characteristic that influences the final forecast of End of Service Benefits. Finally, an additional characteristic studied is the Product Life cycle stage of the company. This is analyzed in order to choose a suitable forecasting method. Based on the literature, the company at the introduction stage will have to use qualitative methods to forecast sales due to the absence of historical data. Similarly for the growth stage, statistical techniques are used to identify rapid growth trends and time series analysis or life-cycle analysis are used when it is at a steady-state (Chambers et al., 1971). The product life cycle is also helpful to explain the company's sales, marketing characteristics, and product divisions. The results show that the company shows characteristics of both growth and steady stage. Hence statistical techniques that identify trends, time-series statistical methods, combined qualitative and quantitative methods should be used. On reflecting back to the main research question, the characteristics of the SFM framework specific to the organization are studied to understand its influence on the forecasting process and improve it.

   (b) Sales Forecasting Capability
   As mentioned in the SFM framework, information technology and process were considered as an important elements since they proved to have a huge impact on the data collection, data analysis, and building the quantified forecast model. The results show that the main software applications that were used extensively were Salesforce, Google Cloud Platform, Tableau, Excel. And cross-functional communication is crucial for effective sales forecasting. Throughout this study, there was a constant collaboration with professionals from different teams like Sales Planning, Sales Operations, Business Analysis. The data collection and retrieval process, knowledge about sales compensation structure, and sales department estimates were gained via cross-functional communication.

   The characteristics that influence the sales forecasting management are explained which accounts for the answer to the first sub-research question. Finally, in the summary of chapter 4, the SFM framework from the literature is compared against the modified SFM framework 4.5.

   On using the above-mentioned organizational characteristics, different forecasting techniques were tested and an appropriate method was chosen which provides the answer for the second sub-research question.

2. **What is the appropriate forecasting technique that predicts sales for the given high-tech industry (Palo Alto Networks)?**
   Following the first question, the forecasting technique forms the important component of the sales forecasting capability of the organization. The first step is the data collection and a research design (5.1) is used to define the unit of analysis and the unit of observation. The historical bookings exhibit a seasonality between the bookings made by different sales employees but the seasonality is not repeated every fiscal year as shown in 5.2. Based on the organizational characteristics, a literature review

was carried out to shortlist the forecasting techniques that suit the product life cycle stage of the company, simplicity to be used by cross-functional teams, ability to be built using the abilities of software applications like Salesforce, GCP and Excel and the results are mentioned in the section 3.2. Different forecasting methods as shown in 2.2 were validated and its results show that the combination of sales department composite (qualitative method) with quantitative analysis produces the best sales forecasts as shown in the 5.9. The exponential method 5.2 has good accuracy but it cannot be used to predict bookings made by new sales employees. Other methods like moving average (Figure 5.1) had less accuracy and it cannot be used for medium-term/quarterly financial planning as it requires the actuals of the recent three months. Regression proved to be insignificant which shows that the correlation between time horizon and the sales bookings is not significant as shown in figure 5.3. Hence for qualitative analysis, variables other than time (fiscal month) were studied. The variables are provided as input by the sales employees and it is recorded as an opportunity in Salesforce. On analysis, it was observed that the age of an opportunity and the total amount of a booking has an impact on sales. A regression analysis was carried to check the significance of age and amount on sales bookings as mentioned in 5.6. There was a significant effect of age and amount for a booking to be successful. And it's effect was quantified by defining a probability function based on the historical successful bookings as given in 5.6. The variables that are considered in the final model were employee, age, and amount. The employee was included to improve the accuracy since the sales target and the sales performance depend on the years of experience of an employee. Finally, the model predicted sales with an average variance of 34% (Fig: 5.8. Hence the qualitative method of sales department composite combined with the quantified probability function based on age, amount, and employee is the appropriate method for sales forecasting.

3. **What is the effect of sales forecasts on the business performance (end of service benefits)?**
   The sales bookings are predicted using the above-mentioned model and the model is extended to predict the commissions of the employees. Currently, the organization is using the On-Target Incentive as the commissions received by the employees. Hence the predicted and OTI commissions are compared with actual commissions. The results from figure 6.1 show that the forecast commissions have less variance of 24% when compared to the OTI (-55%) (Fig 6.2). This shows that the quantified sales forecasting model is better than assuming OTI as the commissions.

   Further, the commissions model is extended to predict the End of Service Benefits. The results show that the EOSB forecasts from the predicted commissions (the result of the sales forecasting model) have very high accuracy (-2% variance) when compared to the EOSB predicted using OTI as the commissions (-57% variance) as mentioned in the figure 6.3. This shows that the quantified forecasting model built using the modified SFM framework can be effectively used to predict the business outcome (EOSB) and it also improves the forecasting process. Hence by increasing the accuracy of the forecasts, the organization can improve its financial planning process which in turn has an effect on EPS and stock value.

The results show that the components of the sales forecasting climate in the SFM framework influence the sales forecasting performance since it is an important criterion to consider while choosing the appropriate forecasting technique. Further, the information logistics and the cross-functional communication component of the sales forecasting capability have a huge influence on the data collection and forecasting performance. Without the integrated information logistics, and the knowledge transfer among sales employees, sales planning, business analysts, and financial analysts, it is non-viable to collect the data and build the model efficiently using the available tools within the organization. The components as mentioned in the modified SFM framework (fig: 4.1) are validated to have an influence on sales forecasting management and thereby the final performance outcome of End of Service Benefits.

Finally, the insights gathered from the sub-research questions are gathered and reflected back as a feedback loop for the top-level executives. As mentioned in section 6.3, the top-level management should provide an organizational climate that supports and encourages collaboration and effective use of information logistics.

The table 5.8 gives the accuracy of the sales forecasting model and it has better accuracy when compared to other quantitative methods as discussed in chapter 5. The tables 6.1 and 6.2 prove that the commissions predicted as a result of the sales forecasting model and the modified SFM framework produce better results when compared to the current forecasting method of assuming On-Target Incentive as the commissions. The sales compensation structure as mentioned in the sales forecasting climate, information logistics of the sales forecasting capability has improved the sales predictions when compared to the current forecasting technique used at the organization. Further, the final business outcome predicted is the End of Service Benefits and it has a very low variance of 2% when compared to the one predicted using On-Target Incentive (-57%). This proves that the modified SFM framework has improved the forecasting performance of both the sales and the operational expenditure of the company which impacts the business performance of the company. Hence by including the impact of sales compensation structure and external factors such as Labor Law, it is possible for a high-tech organization to predict the End of Service Benefits entitled for its employees. But as mentioned in the thesis, it is important to have an integrated network of software applications that supports cross-functional knowledge transfer and data flow. Finally, the step-by-step procedure undertaken to realize the forecasting model is explained in the figure 7.1. These steps provide the direction to implement and effectively use the forecasting model in the future by the organization. By using this model, it will help the organization to improve the accuracy in predicting the sales and the End of Service Benefits.

7.2. Relevance of the Study

The results show that the quantified model of the SFM framework as mentioned in 6.4 improves the sales forecasting management at a high-tech industry such as Palo Alto Networks. The thesis study is applied research done as a case study at a leading cyber-security industry. But it is important to discuss the generalizability of the quantified model and to address the novelty of the research. The generalizability of the research can be explained using the following conditions:

The model can be used for high-tech industries that show turbulent and dynamic sales bookings as it is based on the characteristics provided by the sales department estimates but not the time horizon. It is generalizable for the companies that use high-tech IT software applications like Salesforce, Cloud Platform, data management tools like Tableau, and ERP systems like SAP as mentioned in 4.1.2. Further, the model can be used for companies that have a product life cycle at a growth or steady stage. It cannot be used for start-ups due to the absence of historical bookings data that are explained in detail in the section 4.2 which has PLC characteristics similar to Palo Alto Networks as given in table 4.3. To summarise, The model can be used for companies that provide an organizational climate that encourages collaboration and it is suitable for a company that uses the salesforce that provides data about every sales opportunity. The model can be used if there is a high dependence on sales employees' estimates on the forecasting performance. More specifically, this model can be used if there is an evident impact of age and amount in a sales booking to be successful. Hence it can be used for a company that has an organizational practice to religiously record the sales bookings details the moment the sales employee is in the first line of contact with a customer. The sales commissions model and the extended EOSB model does not have generalizability since it is based on the company-specific compensation structure.

The novelty of the research is discussed as follows: The effect of sales forecasting performance on End of Service Benefits has not been studied before and the thesis addresses this gap. The SFM framework mentioned in the article (Davis and Mentzer, 2007) is a theory-based framework and it has not been quantified and validated in an organizational setting of the high-tech cyber-security industry which has been the main aim of the thesis. The forecasting model has been developed from scratch and is based on the empirical setting, characteristics, and trends of the organization.

This work, like any scientific research, has limitations. The model is highly dependent on the sales department estimates. The parameters like opportunity closed date is a tentative date that the sales employee predicts the opportunity to be closed. Secondly, the total amount of an opportunity can also differ since the customer can end up buying more products or less. These inaccuracies can be reduced by using rolling forecasts and retrieving the opportunity data at regular intervals to get the latest updates on the opportunities. Further, this shows that the employee has the responsibility to update the fields regularly on the salesforce website regularly in an event of change. This practice should be encouraged among the sales personnel. The results from the forecast model 5.8 shows a huge variance at one particular instant which is highlighted. This is because the probability predicted to close the opportunity based on the age, amount, and employee combination. But that opportunity was actually lost. This shows that in rare cases, the results of the model have high variance. This can be reduced by including the sales pipeline stages as discussed in the chapter 5.

The thesis also finds that the SFM framework has to be adjusted to include the sales pipeline stages as an important organizational factor that influences sales forecasting management. The sales pipeline stages should be included in the sales forecasting climate of the SFM framework and the importance of sales employees' estimates should be mentioned as a characteristic under the credibility of sales forecasting (Davis and Mentzer, 2007). Thus, the thesis captures an important gap in the SFM framework 3.1, and provides an interesting insight to include the sales pipeline stages and the sales employees' estimates in the framework to improve the sales forecasting credibility.

7.3. Directions for Future Research

Considering the limitations of the work, the following directions are provided for future research. From an academic perspective, the Sales Forecasting Management (SFM) framework should be modified to include the sales pipeline stages as an element. The impact of sales pipeline stages on the sales forecasting process can be qualitatively measured through interviews with different organizations in the high-tech industry. Further, the framework can be quantified and validated across different industries. The thesis exhibited the relationship between age/amount on sales bookings. This relationship can be validated in a different organization within the same industry or a different industry. The business outcome assumed in this thesis was End of Service Benefits, the framework and model can be extended to test the impact of sales forecasting on other business outcomes.

From a managerial perspective, the model can again be improved to include sales pipeline stages into consideration to define the probability function. The model can be replicated and validated for other units of observation - different regions other than the Middle East and different theaters other than Europe, the Middle East, and Africa (EMEA). Further, in this study the sales forecasting model is used to predict End of Service Benefits which is based on employees' salaries. Hence part of the model can already be extended to predict the salaries of the sales employees throughout the organization.

To summarise, to be able to generalize the findings in this thesis, confirmation by further studies is needed. Both qualitative and quantitative research should be carried out to develop the Sales Forecasting Framework and to quantify its impacts on different business outcomes. Hopefully, this thesis has suggested the directions for improvement of the SFM framework and sales forecasting model which can act as a starting point for further research.

7.4. Self Reflection

This research complements existing literature by presenting something new about the Sales Forecasting Management (SFM) framework and the forecasting methods that were tested under the organizational setting of a high-tech cyber-security industry such as Palo Alto Networks. The thesis demanded to have a strong theoretical knowledge of sales forecasting management as well as good IT skills. This thesis has helped me to improve my technical IT software skills to a great extent as it involves working and analyzing with a huge amount of data. Further, I personally found the thesis to be very interesting and very relevant to MOT as I was able to understand and explore and understand how firms can use technology to design and develop sales forecasting practices that contribute to improving outcomes such as forecast accuracy, profitability, and to some extent competitiveness. This study shows an understanding of information logistics from a corporate perspective using technology as a corporate resource. Furthermore, the MOT concepts such as Product Life Cycle (PLC), research methods - correlation and regression served crucial to perform this study. Finally, through this thesis, I gained an understanding of the importance of sales forecasting practices for an organization's financial health. I could have still explored the impact of sales pipeline stages in forecasting performance and developed a forecasting model with much better accuracy. But due to time constraints, this was not investigated very extensively but has been included as a direction for possible future research.

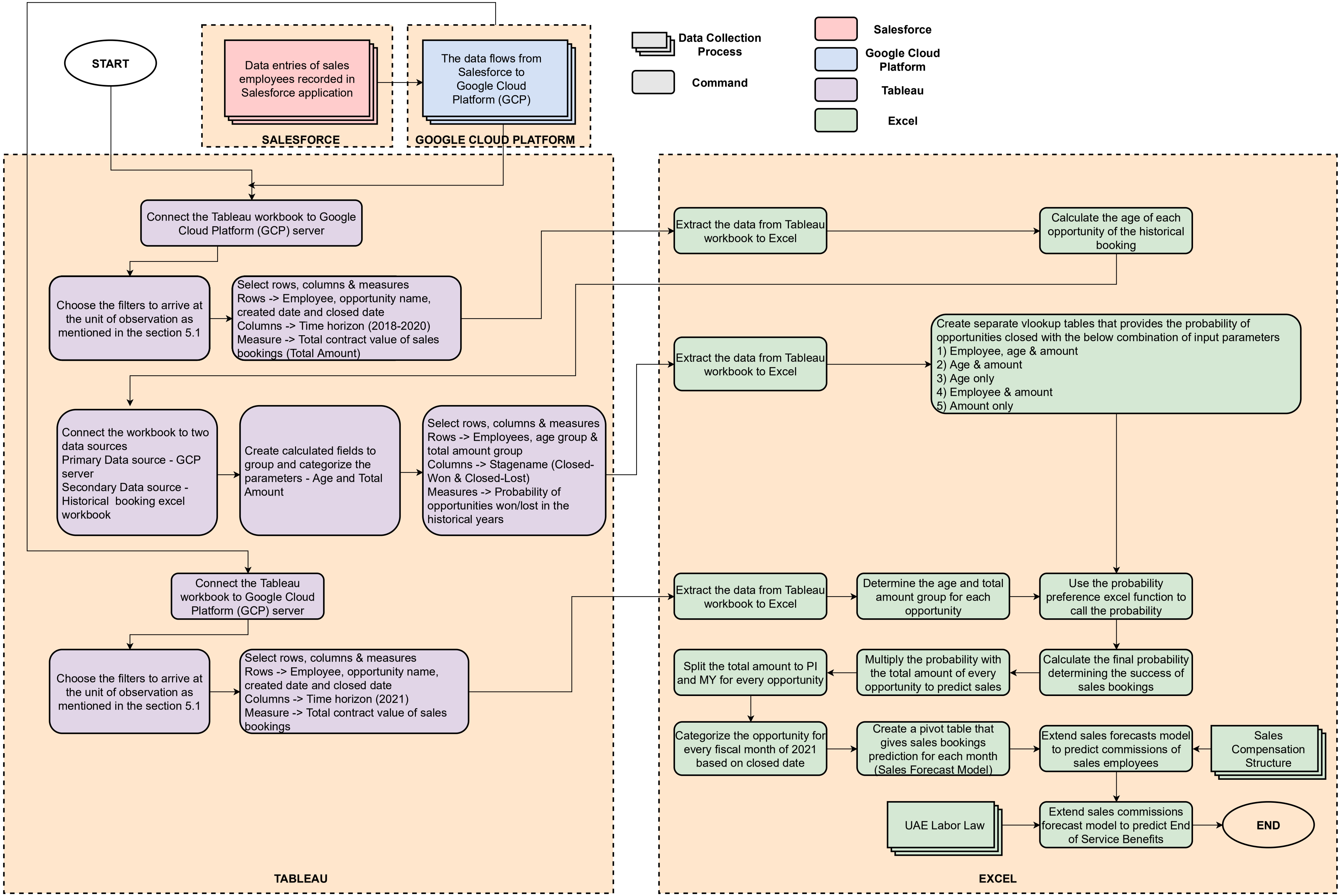

Figure 7.1: Step by step procedure to realize the forecasting model
Note: The diagram explains how the data is retrieved from the application, how it flows across each application and the steps carried to build the forecasting model.

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