The impact of Artificial Intelligence within a digital sales environment: A quantitative view of salesforce automation adoption and perceived value.

Daniel Cousineau

MBA

National College Ireland

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Abstract

Background: Artificial Intelligence is the engine driving the 4th industrial revolution and is at the forefront of global digital transformation across all industries, the global AI market is expected to be worth up to $15.7 trillion by 2030 (Brauer, 2019). Over the last decade businesses have actively invested in AI to create a competitive edge, the sales function is no exception.

Purpose: The purpose of this paper is to investigate the perceived value of AI within a digital sales environment, whether the adoption of AI is impacted by the experience of tenure of a sales professional, and will training of an AI tool influence adoption.

Methodology: A cross-sectional, research design using a quantitative survey method was used to investigate the impact of AI in a digital sales environment within the technology sector. Specifically building on the current literature in relation to perceived usefulness. The data for the quantitative analysis was collected from 41 respondents through a structured survey. The SPSS software was used for statistical analysis.

Findings: The findings of this research revealed that sales executives in a digital sales environment are adopting AI and perceiving the technology to be valuable. In addition, tenured salespeople are adopting the new AI technology, despite conflicting literature. Finally, a formal training structure is not required or has no substantial baring to improve the adoption rate of salesforce automation tools. This paper adds to the existing literature in the field and supports evidence that organisations risk future market share by not leveraging AI across the sales business function.

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Chapter 1: Introduction

Over the past decade, Artificial Intelligence (AI) has become a prominent engine in driving the Fourth Industrial Revolution. It is rapidly becoming a technological force affecting all disciplines, economies, and industries (Madzou, Shukla, 2019). The global AI market is expected to be worth up to $15.7 trillion by 2030 (Brauer, 2019).

AI is not a new field; the term artificial intelligence was formally coined in 1955. However, development pre-2010 was restricted.

- In 1959 the first self-playing game programme was created.
- General Motors added their first robot to the production line in 1961.
- The first natural language bot was created in 1965.
- 1974 saw the first autonomous vehicle created in Stanford Lab.
- 1997 IBM's Beep Blue beats a chess champion.
- 2010 Google announces a self-driving car (Frey & Osbourne, 2013).

Albeit slow, advancement of AI continued through the last 70 years. However, today the progression of AI is growing at an unprecedented pace. Algorithms leveraging ever-faster compute power combined with the explosion of digital data and the speed of communication infrastructure, has put technological investment at the forefront of business strategy (JP Morgan Chase, 2020).

It is the author's belief that a commercial entity cannot afford to ignore the underlying economic benefits from adopting AI technologies, however there are also many ethical implications such as potential mass job replacement that needs to be considered. Daugherty (2019) argues that AI is not going to replace the workforce but enhance it. This could be true for jobs that require complex 'human interaction & emotions', however, a brief look on an internet search engine can reveal the acute transformation of robots replacing humans in the workforce through automation. The forecast is for this to drastically increase over the next decade (Oxford Economics, 2019).

AI now sets the prices on Amazon's online store, qualifies buyers for financial loans and suggests songs on Spotify. Recently there was a breakthrough as we witnessed a machine detecting cancer in human patients more efficiently than highly experienced radiologists (McKinney et al, 2020). It can be argued that from a consumer perspective, artificial intelligence is becoming more and more integrated into everyday life – over 20% of UK households now own a smart speaker or voice assistant (Kinsella, 2019).

By not adopting AI, companies may miss the opportunity to stay competitive and could see drastic business consequences in years to come. One area of business that could be greatly impacted by AI is the sales function. UK organisations that are currently leveraging AI are on average performing 11.5% better than those who are not (Brauer, 2019). After analysing the McKinsey Global Institute data on 'automatability', Baumgartner et al. (2016) suggests that 40% of the tasks undertaken by sales professionals can be automated. AI will support the salesperson by taking care of the mundane tasks like contract creating and lead generation, giving more time for the seller to focus on elements of the sales process that requires the 'human touch'. "The majority of a sales rep's time (63%) is consumed by non-revenue-generating activities. AI has enormous potential to free up sales reps' time so that they can focus more effectively on selling, building relationships, and closing deals" (Fatemi, 2019).

The author's purpose for this thesis is threefold:

1) to investigate the perceived value of AI within a digital sales environment.

2) to investigate whether the adoption of AI is impacted by the experience or tenure of a sales professional, and

3) will training of an AI tool influence adoption.

Although there is evidence to suggest organisations are investing in AI to support growth in a B2C (Morrison & Marcotte, 2019). The research conducted in this paper is in the context of a B2B selling environment and aims to examine the impact AI is having for sales executives.

1.1 The AI Tool (Lead Recommender)

The sales function is undergoing a time of profound digitalisation powered by machine learning. The AI tool discussed throughout this paper falls into the AI category of an Artificial Neural Network. Using complex algorithms, a sales tool can surface leads to a sales executive based on a tiered scoring system. For the anonymity purpose of this paper, the author will refer to the tool as 'Lead Recommender'. In addition, the discussion will not expose the company in which the research is conducted but will state that it is a large technology firm. The organisation provides a large range of technology solutions, has invested heavily in a digital sales environment, and has subsequently built the AI tool with its own IP for their sales executives.

Lead recommender is an intelligent lead-scoring application that sources leads to sales executives that have the right propensity to purchase based on interactions. The tool progressively learns which leads are relevant and which ones are not, in turn, reduces the amount of time sales executives spend qualifying the leads. Once a lead is surfaced, the application provides personalised content and marketing templates that each salesperson can send directly to the prospect. This saves the salesperson from spending time creating their own content and researching sales offers. The leads are only generated once enough information has been captured and the potential customer has given consent to be contacted. The information surfaced could be a mix of activity such as signing up to product webinars, attending events, downloading whitepapers, and starting product trials. These occurrences are known as marketing interactions. The more marketing interactions a prospect has engaged with, the bigger the propensity score. There are many data points that can influence a higher propensity score, for example, if there are several marketing interactions over a shorter space of time, this is surfaced as a higher propensity as it would suggest the prospect has a larger desire to find out more about the specific product or solution. Once the propensity score has reached a certain point the lead will surface as an action for the sales executive to follow up on. This tool is the basis for all the research conducted and the subsequent discussions outline its perceived value by sales executives.

It is important to recognise the maturity of the lead recommender tool. The tool was launched as an internal resource alongside the formation of the a new digital sales model, it has been used daily by over 700 sales executives since July 2017 and this is just the local operations. There are also digital sales operations in US and APAC consisting of similar employee numbers.

In the last 3 years, the machine learning algorithms for the tool have been exposed to a large input of data signifying which recommendations are valid and which are not. This input of data has allowed the tool to learn and improve the accuracy of a ‘valuable recommendation’. Unfortunately, there is limited data available into the quality of leads accepted by sales executives over the last 3 years, but the author can say with confidence that there has been a vast improvement of lead acceptance as the tool has matured.

1.2 Research Questions

The author wanted to systematically measure if using the tool, offered sales executives an experience that was congruent with generating business more efficiently. Can sales executives’ surface better data to begin the sales process with AI than without it?

The literature review will outline different views on adoption of sales automation tools and their perceived use. However, the author wanted to combine the research purpose with both the ‘perceived value’ of lead recommender and the impact of adoption based on sales experience and tool training.

Research Questions.

1). Does AI have a positive perceived impact in a digital sales environment?

2). Will the adoption of AI tools be negatively impacted by sales tenure?

3). Does training influence the perceived usefulness of AI and adoption?

1.3 Hypothesis

Homburg, Wieseke and Kuehnl (2010) define perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance." The author has constructed a survey that logically asks participants to rate their adoption and personal attitude of the tool, their perception of value, and their training/onboarding experience. These three sections of the survey consist of 14 questions and draw an interesting perspective on the correlations between them. The author wanted to gain insight into the three research questions and based on previous literature had formulated the following three hypotheses.

Hypothesis 1 (H_1)

> The higher the lead recommender tool adoption rate, the higher the perceived usefulness will be. The nature of the tool is to learn. Consistent feedback from the seller to the tool will train the models and source highly accurate leads as more data is fed into the machine.

Hypothesis 2 (H_2)

> The more sales experience a sales executive has, the lower the perceived value of Lead Recommender will be.

Hypothesis 3 (H_3)

> Sales executives with less training of the tool will have a far lower adoption rate and therefore will have a more negative view of its usefulness.

These will be the three key points the author will refer to throughout this paper, and the data collected will spark an interesting discussion on where future research could focus.

1.4 Thesis Structure

The first chapter gives a brief introduction of AI and why this is becoming a prominent discussion across many areas in business. In addition, the reader should understand the research question and the reasoning behind the hypotheses. Chapter 2 condenses the literature around AI and sales to give more context to the research and why it's important. Chapter 3 discusses the research design and the methodologies and chapter 4 will outline the findings and discuss the limitations. The thesis will close with a conclusion and suggestions for further research.

Chapter 2: Literature Review

2.1 Introduction

An article in from the Harvard Business Review revealed organisations using AI in sales were able to increase their sales leads by more than 50% and recognise 40-60% cost reductions (Baumgartner, Hatami and Valdivieso, 2016). From the article there are two underlying themes.

1) AI will fundamentally change the sales function, and
2) salespeople will need to work with AI and develop "machine intelligence."

It by no means extensive and lacks explanation of how salespeople can adopt machine intelligence, however, they do subscribe to the idea that machines will support in completing mundane and basic tasks, so that the salespeople can focus on more on the 'human touch' aspects of the sales process.

To the author's knowledge there is limited literature in this field, therefore, AI in sales is an exciting opportunity to uncover potentially fruitful insights, within an area that will dominate the sales landscape over the next decade.

There are many categories of AI; chatbots, process automation, IOT, process mining, self-checkout systems, dynamic pricing, voice recognition, marketing analytics, intelligent call routing, predictive maintenance and even intelligent city systems. Most of the momentum is being driven by the large tech firms (Microsoft, Google, Facebook, Amazon, IBM) and currently there appears to be a race for patents as 154,000 were recently filed. This is a compound annual growth rate of 29.3% between 2010-2018 for AI patents (Columbus, 2019).

Knickrehm (2018) identified 5 schools of thought in the debate of how AI will change the work environment. He suggests that leaders who want to position their company to thrive in the future of AI should think about how jobs can be optimised by leveraging AI without displacing workers, in addition, help humans develop the skills that robots cannot fulfil 'the human touch'. They offer the idea that employees in the future will be required to "partner" with intelligent machines to have the most impact.

The author believes that machines can positively impact business processes, however, without a structured adoption plan and transparent leadership communication with employees, firms could see salesforce automation projects rejected.

2.2 Key Themes

There is extensive literature surrounding AI, although it's limited within the sales function context. Technology is fundamentally transforming the sales environment, from social selling to lead scoring. It is also supporting sellers to become more effective at generating and closing revenue. Before discussing the role of artificial intelligence within the sales function, it is important to discuss how AI and machine learning have been defined within the literature.

Michael Haenlein and Andreas Kaplan (2019) define AI by "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". It is a term used for the science of getting computers to perform tasks without being explicitly being programmed and it was established as an academic discipline in the 1950's.

AI is the ability of a computer to deal with ambiguity based on previously collected data. Machine learning is an algorithm designed to process data to produce predictive models. The more data that is ingested into the machine, the more sophisticated and accurate the outcomes will be. The best way to think of this is, machine learning is an approach to achieve artificial intelligence. There are two major types of data (feature and labels) and three major type of machine learning algorithms (reinforcement, supervised and unsupervised). Supervised learning models have algorithms that learn the relationship between the input (features) and output (labels) data and look to replicate that model. Using artificial neural networks (ANN) the 'Lead Reccomender' application will understand the desired propensity of a buyer from a sellers perspective, and surface leads accordingly.

Leveraging artificial inteligence is a way for businesses to differentiate themselves. Homburg, Wieseke and Kuehnl (2010) report the extensive use of AI within the corporate environment and that adoption is growing. The main challenge for organisations that are not already using AI but express a large desire to invest, is the lack of in-house digital skills. Organisations are actively pursuring development of support vector machines, artificial nueral network and natural language processing models to improve sales automation, however models need extensive training and fed hundreds of terabytes of data before the technology can be packaged and commercialised which makes it a stimulating and current topic for future research. *Figure 1* shows the adoption rate of AI based technology from a global survey across sales and marketing professionals in 2020.

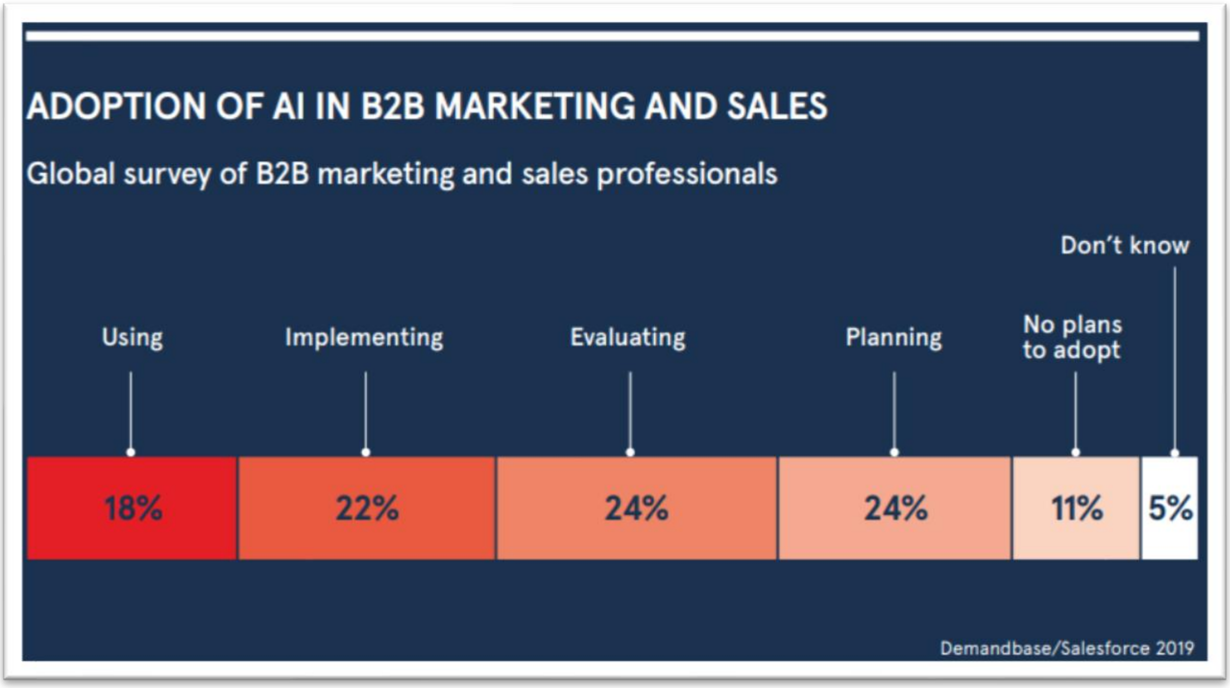

Figure 1. Source: Demandbase/Salesforce, 2019

Syam & Shama (2018) is one of the most comprehensive papers in relation to AI in sales, they give simple explanations to the machine learning models and the potential use in sales, they have understood that the sales role is changing because of technological demands, thus introducing the idea of salespeople are now like "knowledge brokers". In addition, they have given a great framework for future research and subsequently labelled that research in relation to the 7-step-sales-model that will be discussed later. However, their research is by no means extensive and prodominantly just provide a framework for future research to focus.

2.2.1 Digital Sales

In the last two decades the sales landscape has changed. The explosion of data has meant that information is now more accessible than ever before and this trend is now slowing down, the IDC estimates that in 2025, the world will create and replicate 163ZB of data (Reinsel, Gantz and Rydning, 2017). Customers are more informed before entering the sales process and therefore sales methodology has started to pivot. Jones et al (2005) suggests that today's sales knowledge hinges on models that are no longer relevant. In line with Syam & Sharma's (2018) point regarding categorisation of salesforce and the potential use of AI, this research will focus on digital sales executives in relation to stage one of the sales processes (Prospecting).

Sales processes respond to changes in the larger macro environment (technological, macro-economic, demographic, cultural), for example, phones and fast travel changed the sales engagement process of the stereotypical travelling salesperson (Syam & Sharma, 2018). As the demands of the customers change, sales teams increase the usage of technology to keep up with the demand. Traditional sales models required field sales executives to often meet clients face to face and inside sales to handle more administrative tasks. It could be argued that the field sales role required more experienced professionals, as sellers are expected to present and show product value to customer stakeholders in a more complex solution sales engagement. In addition, it could be necessary for the field sales executive to travel extensively and therefore the costs associated to those type of roles is usually higher. Inside sales (or digital sales) has previously been compared to a call-centre type environment, where a sales executives duty's involve spending hours per day on the phone making cold calls and sending emails to follow up on sales leads. However, as the digital sales role matures and the technology improves, there are increasing examples of experienced sales professionals filling those roles. In addition, the rapid adoption of video conferencing technology has resulted in less face-to-face meetings which in turn, reduces the travel-time requirement by traditional field sales executive, therefore presenting opportunities for organisations to merge field roles into digital roles and reduce costs. Moreover, as customers become more knowledgeable due to the amount of readily accessible information (Homburg, Wieseke and Kuehnl, 2010) there are growing examples where large complex deals have been won without any requirement for seller and customer to meet physically.

The advent of the internet has brought wide-scale availability in communications and collaboration tools. Email is almost 50 years old but it is still a prominent technology for communications between sales executives and their clients, research conducted by Singh, Marinova and Singh (2020) posit that in today's sales environment, email is used by sales executives at every stage of the sales cycle- from prospecting to closing. Their research not only suggests email is still widely used but still very effective. They build upon two conceptual models for e-communications and show evidence that in a B2B environment, the use of email communication is preferred. Sales executives can take the time to build in "textual cues" to grab buyers' attention which contributes to a greater likelihood of contractual award. However, unlike face-to-face, it is harder to build report or social bond through email communication and therefore, the author foresees AI advancement supporting sales executives building that introductory rapport with personable insights. A potentially highly valuable business proposition for organisations to adopt.

Sales digitisation expands the role of technology to create efficiencies for the salesforce, it is not uncommon for sales executives to be engaging with lots of different salesforce automation (SFA) applications on a daily basis. These SFA applications include but not limited to "contact management, enhancement of sales presentations, automation of administrative tasks, strategic information exchange throughout the organization, and computer-based training" (Davis, 1989). Technology has had a profound impact on the sales function, and as technology continues to advance, companies that not incorporating AI are likely to miss a competitive edge (Brauer, 2019).

2.2.3 Salesforce Automation (SFA)

Salesforce automation can be defined as a process in which a business task of sale becomes automated. In general, salesforce automation is implemented to improve an organisation's sales process or enhance the experience of the buyer. Examples of this is vastly wide-ranging, from using chat bots on a website to streamline an order process, inventory monitoring and control, order tracking, customer management, sales forecast analysis and employee performance evaluation.

A review of the literature reveals that the leading theory applied to the challenges of salesforce automation adoption is the Technology Acceptance Model (TAM). The TAM is a model that theorises users' acceptance of technology and predicted adoption by end users. The model puts forward the idea that technology adoption is linked to two key factors, 1) Perceived Usefulness and 2) Perceived Ease of Use (Davis, 1989). Prior research not only suggests that the introduction of a new tool needs to be easy to use, but also users also need to receive support, training and guidance to the implantation to be accepted. In addition, there is empirical evidence to suggest that sellers are more likely to adopt new technology if they see their superiors and peers using it (Homburg, Wieseke and Kuehnl, 2010). The author aims to advance this literature by ascertaining the perceived usefulness of the lead recommender tool.

Homburg et al (2009) seeks to advance the salesforce automation literature and their paper explores levels of adoption of automation by salespeople. They suggest social influence is important when it comes to the adoption of SFA tools and the key finding is leaders and superior's SFA adoption affects salespeople's SFA adoption. However, they do not define the tool itself and what category of algorithms are used, in addition, they do not define which area of the sales process the tool resides in. Mariadoss *et al.* (2014) shows empirical evidence that SFA influences competitive intelligence behaviours which in turn will improve the sales performance. The AI tool used in the context of their research resides in the first sales step of the seven-step sales process (prospecting). The tool surfaced product knowledge, industry insight, product presentations for sales executives to leverage for pre-call planning. Their research adds to the theoretical understanding of competitive intelligence and SFA, they conclude that SFA improves sales performance and users perceive the AI tool as valuable. However, this research is limited to one company (in the bio-tech industry) and the tool itself is not an extensive AI tool.

2.2.4 Adoption of AI

The last century has seen multiple iterations of manual job replacement through automation. Factory floors have been leading the way for years in relation to streamlining manufacturing jobs. Mckenzie (2015) offer linear examples of job replacement through the adoption of AI, the Ford Motor production line established in 1913 in Michigan required over 140 workers to produce the Model-T automobile, over a decade later, Ford now operate production with over 20,000 robots to do the heavy lifting or the less-desirable jobs that require far less manual labour. AI has profoundly contributed to job replacements and this is mostly evident in the manufacturing sector, in the UK, PwC "estimates the number of jobs in the manufacturing sector could be reduced by around 25%, signifying a loss of roughly 700,000 jobs" (PwC, 2018). As a result, the idea of regulating the adoption of AI is now being discussed by scholars, as an example firms could be made to train employees for new jobs with the money saved through automation. Therefore, we can conclude that AI will have a profound impact on future jobs.

Huang et al (2019) suggests AI is expanding beyond mechanical and repetitive to analytical and thinking. This supports the authors' view that AI will give salespeople more freedom to work on interpersonal and empathy-based tasks. They suggest the most successful companies will take advantage of this 'Feeling Economy' trend. It will threaten some jobs, transform others, and create new ones, thus managing feeling intelligence could become a competitive advantage. Their theory and research implies that there are less jobs that require mechanical and repetitive tasks as shown in *figure 2* and forecast that AI will eventually move into feeling based jobs by 2036, however the description around AI and humans working together is very limited and does not go to great length to describe importance of salesforce adoption to make these predictions a reality. In addition, as AI starts to have a profound impact on jobs in the economy, local governments and leading technology councils may choose place sanctions to limit development to keep in line with employee expectations.

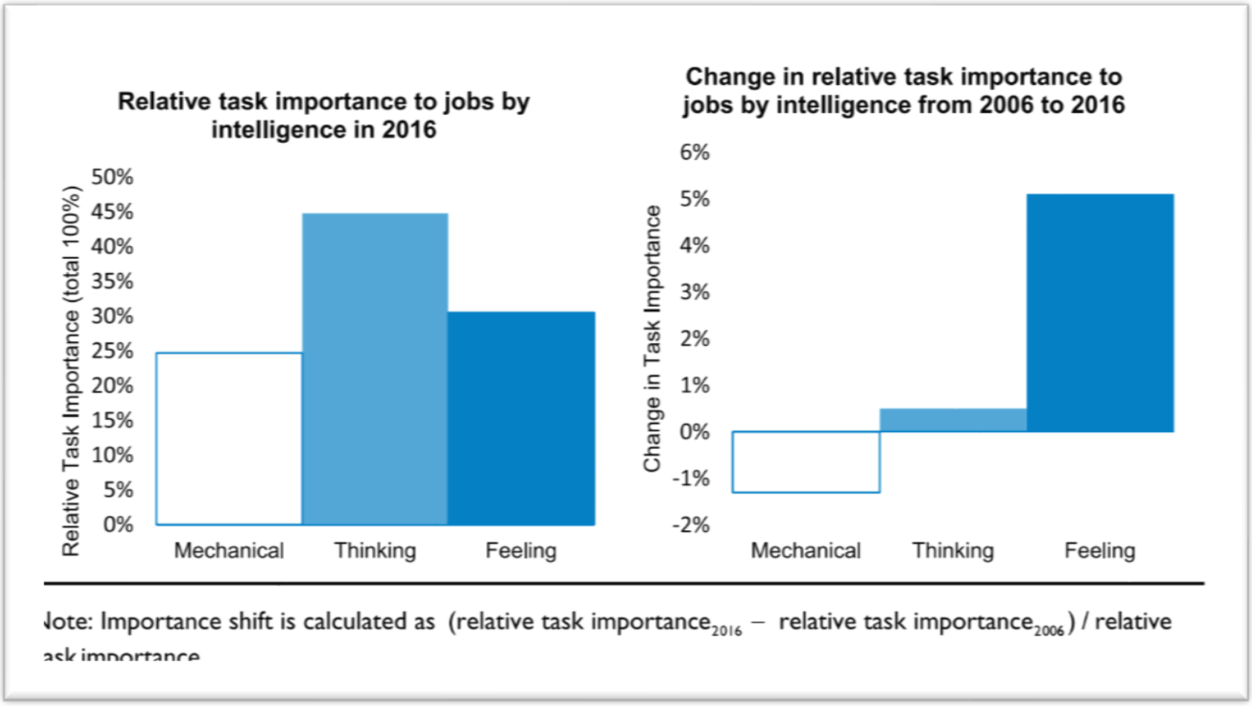

Figure 2: Huang et al, 2019

Another factor that can affect SFA adoption is employee stress. Rangarajan et al (2005) conducted a cross sectional study among 154 salespeople that found stress can have a negative effect to adopting new tools. They found that a key contributor to increase stress is task complexity, for example, if the tool is complex and is not easy to use, the adoption rate will not be as high. Holt (1998) state that “salespeople are not comfortable with technology and just want to sell”, therefore contributing to H2 that tenured sales executives could see the Lead recommender tool as ‘another admin task’ to complete on top of their day-to-day selling activities resulting in diminished adoption.

As organisations invest and adopt more automation technologies, it’s not inconceivable to expect an amount of animosity from employees that may anticipate their jobs being replaced by AI. Jim Dickie (2018) discusses his experience of presenting to a sales team in a Fortune 100 company about the technical innovations that AI could bring, it concluded with questions relating to fear of job replacement more so than the future upside of sales professionals adopting said technologies. It is important that as this new wave of technology becomes embedded into the daily lives of sales executives, senior managers continue to reassure employees that the benefits gained far outweigh the negative connotations associated to accepting and adopting SFA tools. This literature helped to frame H2 as the author subscribes to the idea that tenured sales executives will view AI as a potential threat and thus the adoption of the lead recommender tool will not be favourable.

2.4.1 Tool training

Recent literature suggests that the adoption of SFA tools are not always widely accepted by salespeople and research indicates that there are lots of variables to consider when a firm is to implement a new SFA tool. Homberg et al (2009) explores levels of adoption of a new automation tools by salespeople, they suggest that social influence is an important variable when it comes to the adoption of SFA and their key finding is sales leaders and sales managers adoption influences salespeople's SFA adoption. In addition, the study also provides evidence that training was not always adequately provided to salespeople that expressed high adoption rates and therefore would suggest that social influence plays a bigger part in SFA adoption than a robust training programme. However, the evidence in the study by Ahearne, Jelinek and Rapp (2005) shows inadequate training will have a damaging effect on the adoption by salesperson and subsequently conclude that managers need to invest time to support salespeople in tool adoption. Contrasting the these two important studies, there is empirical evidence to suggest that training on new tools will enhance SFA, however there is also a time investment required from managers and peers to ensure the successful adoption by salespeople. One limitation of both these studies is that they were not longitudinal studies and the tool was not in place more than a year, thus not considering the 'ramp' period. A period that gives salespeople time to understand and adopt the tool, this could be three months or could equate to 18 months.

Drawing again from the Technology Acceptance Model (Davis, 1989; Venkatesh & Davis, 2000), an individual's intention to use a system is determined by two beliefs: the technology's usefulness and ease of use (*figure 3*). The model suggests that users will have a predisposition before using the technology. If training is offered, this will influence the perceived ease of use, which will thus have an impact on the perceived usefulness and therefore attitudes and behaviour towards intention to use should increase. Therefore, in line with H3, if a tool training program is in place by the firm, then the perceived usefulness should be impacted positively, and adoption of the lead recommender tool should be higher.

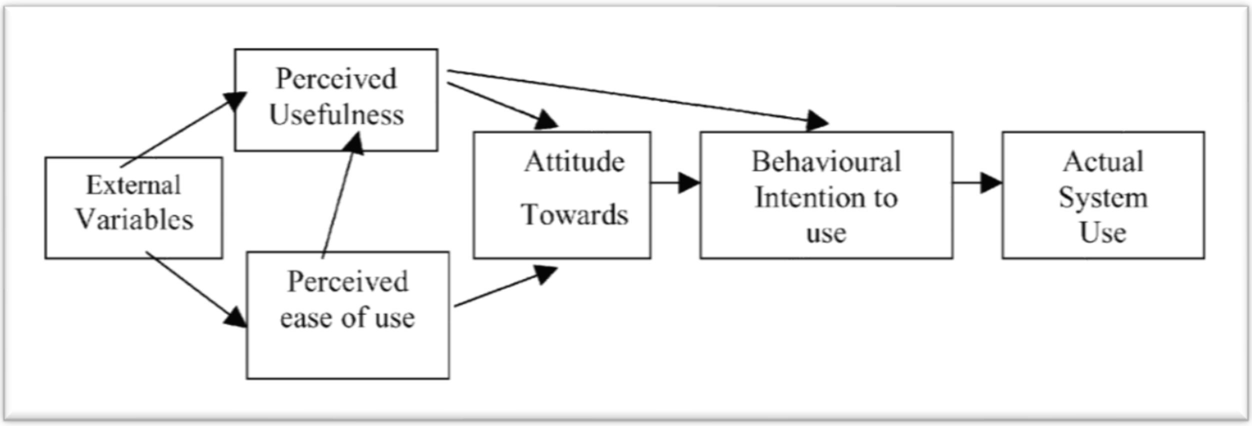

Figure 3: Original Technology Acceptance Model, Davis, 1985.

2.3 The Sales process

This section is to reflect on the historical selling processes and how technology has played a role in enhancing each process. There is a widely accepted sales model consisting of different taxonomies which many scholars have developed over the years. Throughout history scholars have discussed at length the different sales processes and the different characteristics aligned to each sales process or sales step. Wotruba (1991) discusses five distinct selling processes and the characteristics of a salesperson suited for that process based on the historic literature (Provider, Persuader, Prospector Problem Solver, Procreator). Although the stages are well articulated and the article outlines examples of the selling characteristics aligned to each sales stage, the model is not chronologically linked. Moncrief and Marshall (2005) further expand the discussion and reflect on the evolution of the seven-step sales process. This model is chronologically linked and widely accepted. They discuss the steps of a sales cycle and the potential technology use throughout the process and the sales steps are as follows:

1. <u>Prospecting</u>

This sales step refers to the beginning of the sales cycle. At this point potential customers are not aware of the solution they require, just that there is a need to be fulfilled. Mariadoss et al. (2014) research shows empirical evidence that a SFA tool enhances sales performance, however, the description of the tool in their research means the author cannot distinguish the extensive use of AI or weather it's merely a CRM tool.

2. <u>Pre-approach</u>

The pre-approach step is still in the early stages of the sales cycle, however more than a need has been established. In this step, sales executives are gathering as much relevant information as possible to start the approach. This could be industry insights, previous correspondence with the customer, marketing material, product information, contact insights via social media sites such as LinkedIn. Once complete the next step is to approach the potential customer.

To the authors knowledge, the first two sales steps in the sales process are the prominent areas for AI investment in the B2B selling environment to date. Gathering customer intelligence, improved lead quality and producing personalised content for sales executives to engage with prospects is the consistent theme for AI introduction in the sales function.

Moncrief (1986) discusses data points from 1981 that suggests that sales jobs require a range of selling activities. The prospecting sales step is no longer required to be completed by a sales executive and can be outsourced to a 3rd party. Many marketing organisations generate income by creating and nurturing leads for organisations. However, this can be an expensive cost and therefore developing AI technology to fulfil that function can bring that back in-house and save costs.

There are discussions around using AI to predict the percentage chance of a sales win, even before engaging with a prospect (Ray, 2019), however, with the technology still in its infancy, enable that functionality could do more harm for business growth. For example, if a sales executive is looking at sales leads and the percentage chance for a sales win is below 50%, why engage with that prospect at all, and instead, focus time on only prospects with 75%+

predicted win rates. In addition, the AI tool by nature needs to be trained over time with consistent feedback to improve the accuracy of the win percentage score, so its initial conservative scores could encourage the pursuit of fewer customers. There are also a moral implications to consider, is it right that firms adopt this technology, for example, if a law firm used AI to predict the win rate of a case using data from previous matters (type of case, judge assigned, seasonality considerations, precedents set) before accepting a case, could this influence a fee earners decision to take on a case.

3. Approach

The approach is the stage where the engagement occurs. This can be via email, video call or a face-to-face meeting. It is the stage where a relationship is beginning to form, and the sales executives needs to make themselves and their organisation as relevant as possible. There is a wide range of best practices in this area and is an extensive topic for debate. Digitalisation has made this area a relevant topic for research but regardless of the most effective way, the idea is for seller to create rapport with the potential customer. It is often referred to as the develop-strategy stage and to the author's knowledge there is little AI development for this sales step.

4. Presentation

Once the approach has been made and the engagement has been established, the next step is to prove the value of the product/solution. In this stage the sales executive has established the budget aligned to the requirement, the authority to sign off and complete the deal, the need for the product/solution and the timescale to complete. This step often requires the sales executive to showcase their skillset and bring the product/solution life. Helping the deal stakeholders to visualise life with the product/solution through well-articulated presentations and challenging debates, can separate an organisation from its competition. This is often the main body of the sales process and dependent on the solution can take the longest step to complete. This sales step is conducive to the argument of the feeling economy as discussed previously. It would be very hard to replicate the interpersonal skills of a sales executive required to move past this step as machines do not have the ability (yet) to empathise, especially where deal values are €1m+. An AI machine alone could not comprehend the small intricacies that is needed from a personal perspective to gain the confidence level needed by prospective stakeholders to move forward.

5. Overcoming objections

Overcoming the objections can be quite uncomfortable for many people, often it is where sale executives make their money. This step is usually the final piece to putting the stakeholders to buy-in. Challenging the customer and putting their objections to rest is the best way for a sales executive to show their competence and prove that the deal will enhance the buyer's situation. Many textbooks provide insight into objections and how to overcome them, but often it will come down to the simple human emotions regarding trust. Does the buyer believe in the seller, and the product/solution they are buying into?

6. Close

This step is the semantics of the deal. The value has been sold, the buyer usually trusts the seller, how does each party agree a price that is mutually beneficial and what are the terms. Evidence suggest that AI is contributing to price setting by calculating optimal profit margin on a deal however, it doesn't always revolve around price. There are finance agreements to be set up and potential opportunities to build PR relationships are put into the contacts via amendment clauses. Often both parties will complete their CNA (consequence of no agreement) analysis and close on terms that suit. Technological advancements has played a part in improving the efficiencies in each of the sales steps and field sellers are increasing use of video conferencing technology to improve the efficiency of the deal closing process (Homburg, Wieseke and Kuehnl, 2010). Other recent articles discuss how AI is not only helping sales executives with prospecting/lead sourcing, but also in the closing stages of the sales process (Kaput, 2019), however, the research is again scarce in this area.

7. <u>Follow-up</u>

According to Servion Global Solutions (2020), AI will power 95% of all customer interactions by 2025- this includes telephone and online conversations. Often referred to as customer service or post sales engagement, this final sales step is an area that has seen much attention over the last 10 years, especially in the technology sector. The rise of consumption economics requires large technology firms to report not only their earnings, but also the use/adoption rates of the technology sold. In short, it is no longer financially viable for a technology firm to just sell the licenses but increasing important to have the new customers deploy and use the technology. This is because once the technology is deployed, it is much harder for competitors to then sell their products compared to if the customer has not deployed. As a result, more investment in technology towards this sales stage has become evident to retain recurring business and upsell later on and the significance in the technology sector has been brought to the forefront of many wall-street investors (Hewlin, 2011).

In addition, there has been a rise of customer success manager role over the last 5 years, where the role is to help clients deploy and use the technology has become vital to keeping out the competition and upselling existing business to more services at a later date. The decision by a firm to align specific roles to customers, based on their buying cycle has contributed to the diminishing number of field sales roles (Bradford et al, 2010). Organisations are changing sales practices to keep up with the increasing expectations from their customers, and sales executives are adopting more of an 'advisor' role as they progress clients through the sales cycle (Moncrief and Marshall, 2005).

The internet of things (IoT) is a term used to describe a multitude of devices that connect to data sources. As an example, ThyssenKrupp use sensors to surface data and predict when their elevators are due a fault, once detected, a service engineer will be notified and assigned to fix before it breaks, therefore better utilisation of productivity by eradicating the need for routine check-ups which are unproductive. In addition, smart bins are active across the UK, a sensory device put inside the bin that will notify council workers when the bin is full and needs replacing. IoT is also being used within the agricultural industry to help farmers more accurately distribute fertilizer based on soil and crop conditions or "yield data from previous crops" (Beinert, Nies and Schmiedel, 2020). There is a vast range of growing benefits for organisations across multiple industries to get value from data.

Applying this to the sales process, it is not inconceivable for AI to add opportunities and additional value after the initial sale. With traditional sales models this follow-up approach may have be a routine sync with a customer, however leveraging AI and IoT, sales executives can now be proactively notified for upsell opportunities. Taking the connected car for example, new models are now fitted with lots of sensors that once the car is driving, data is being transmitted back to manufacturer. The manufacturer seeing this data can be better prepared for the service when it's due and subsequently recommend extra services that not necessarily apparent in the traditional server process.

Syam et al (2018) examined a small area of sales practice and research based on the seven steps of the selling process. Sales renaissance: focus of sales management will shift from traditional sales functions to new functions that may involve bridging inter-organizational and intra-organizational boundaries. So far, automation in sales has made an impact on routine, standard repeatable activities, in the future it could help to understand customer behaviour in order to design and deliver highly customized offerings. They suggest AI can simulate the buying centre with all its complexities, inform salespeople about the data they use, anticipate roadblocks and pitfalls. However, their analysis does not discuss the relevance of training for the salesperson which this author will look to address in this research. In addition, they refer to selling scenarios but do not discuss at length the roles aligned to a specific sales process.

2.4 Conclusion

Although there is a substantial amount of literature in both the field of sales and in the field of AI, there is a limited research published for the use of AI in sales, more specifically lead scoring and predictive sales. This is partly due to the adoption rate of AI only becoming prominent for businesses in the last decade (Brauer, 2019).

In addition, AI tools has been broadly merged with the term SFA which is not always the same thing. Most of the literature published in the last 10 years suggests that SFA tools and adoption enhances sales performance, but the research does not take the time to thoroughly explain the sales tool examined and the technical nuances relating to AI, therefore, it's hard to distinguish the relevant articles that specifically relate to artificial intelligence. Moreover, the literature stems mostly towards three of the seven sales steps in the sales process - the initial stages and the final follow-up stage of the sales cycle.

The State of Sales report (Salesforce report, 2018) forecasted adoption of AI "is set to skyrocket by 155% over the next two years". This will inevitably entice more research opportunities and therefore the author expects more academic research to be published soon. To the authors knowledge, this is the first piece of research that investigates the perceived impact of AI in sales.

Chapter 3: Research Aims and Objectives

3.1 Introduction

Although the author has decided to anonymise the company in which the research is being conducted, it is important to discuss the context of the company and the industry. The company is one of the largest multinational software and services provider globally – they have operations in over 100 countries and have over 130,000 employees. The global salesforce represents 18% of this number split across field sales executives and digital sales executives. In July 2017, the company outlined its biggest restructure in decades, with a focus on realigning its Sales and Marketing organizations. This realignment brought over 700 employees to Dublin Ireland operating in a digital sales environment, using innovative technology to service customers across EMEA from a digital sales hub. In the last three years, the organisation has rapidly matured and refined sales processes, subsequently enhancing the sales process and the usage of AI. This has made the sales environment an optimal opportunity to conduct research in this area.

The following chapter will address the method and approach to the research. The author will discuss the research onion framework and how this is related in the context of the current study.

3.2 Research Definitions

Saunders, Lewis and Thornhill (2015) define research as 'the systematic collection and interpretation of data with a clear purpose, to find things out'. The purpose is to improve the understanding of a subject with the use of empirical data; it is not mere information gathering. The research process requires the identification of the phenomenon to be explored, conversion of the phenomenon to a research problem, collection and analysis of empirical data and secondary sources of data, and the recording of research findings (Fisher, 2010).

3.3 Research Philosophy

Research philosophy is defined as the "development of knowledge and the nature of that knowledge while considering the assumptions held by individuals when viewing the world" (Saunders et al., 2012).

There are two major ways of discussing research philosophies: ontology and epistemology. Ontology examines the nature of reality and epistemology investigates how one can examine reality (Saunders et al., 2012). This research aims to understand how AI is impacting sales executives in a digital sales environment. The study will adopt the philosophy of ontology from a positivism approach. This approach has been taken to investigate the relationship between the adoption the lead recommender AI tool and its perceived value. For this research, the methods used will solely be quantitative in line with the investigation of a reality (Quinlan, 2011). The researcher reviewed the existing literature and formulated the hypotheses from their readings (theories to data), thus using a deductive approach in the research philosophy. The results support H_1, however show that the data is not consistent with H_2 and H_3. Due to the timescale in which this research was to be conducted, taking an inductive and abductive approach would not have been viable.

3.4 Research Methodology

Due to the research gap, it is difficult to link a similar methodology. However, in a 2018 external study of the impact of AI on customer experience (Kumar, Jain, Deb, 2018) used a quantitative closed-ended questionnaire through Google forms which produced a successful data set.

The researcher used Microsoft Forms to collect primary data through a mono-quantitative method via an online survey. The survey consisted of 14 questions and was designed to understand the perceived value of the lead recommender tool and contrast that to participant's sales experience and training associated with the tool. The questions in the survey were framed based on the theories stated in the literature review and various other theoretical concepts related to SFA. In this research study the dependent variable is the perceived value of the recommender tool and the independent variable is the adoption of the tool, the training provided and the sales experience of the participants.

All sales executives (700 employees) in the digital sales organisation will have access to the lead recommender tool, however the author condensed the survey population size to 300. The exclusion criteria used in the research was due to the nature of some roles not being 'revenue generating'. 300 sales executives are in revenue generating roles as opposed to the other 300 support/technical roles. All participants are based in Dublin and are in one of the three roles below.

1) Account Executive (overall sales relationship with customer).
2) Solution Specialist (focused on selling one product).
3) Demand Response Executive (breadth of products and speed of sale).

Each role has separate KPIs and leverages the lead recommender tool differently. Account Executives are typically the first point of contact for customers, and they'll have a broad range of solutions to sell. Their product knowledge tends to remain at a high level and the lead recommender tool will surface a wide range of recommendations for them to follow up on. A solution specialist will have a deeper level of product knowledge but typically will only focus on one solution area. These two roles operate across a mid-size enterprise market across EMEA (commercial and public sector customers between 500-10,000 employees), and the engagement between the clients and the sales professionals will often have more than five engagements before a sale is closed. A demand response executive's role is more fast-paced and requires a scale approach. The type of engagements with clients and sales executes are light touch and tend to close smaller revenue sized deals at a faster rate. The clients are usually smaller than 500 employees and the idea is to serve those customers with speed and scale.

3.5 Research Design

The research design followed a cross-sectional, quantitative mono-method, deductive approach so that the researcher could statistically analyse the data and allow for precise control of variables over a smaller time scale. The questionnaire was inspired and adapted from previous SFA adoption surveys (Homburg et al, 2009; Davis et al, 1989; Venkatesh, Davis, 2000) as discussed previously. The survey logically asks participants to rate their adoption and personal attitude of the tool, then their perception of value in relation to generating revenue and improving customer service, then finally their tool training/onboarding experience.

Figure 4 shows the design of this research in relation to the research onion developed by Saunders et al (2012). Other methods were considered but were eventually dismissed due to varying factors. For example, one of the ideas was to structure the data collection through a quantitative and qualitative multi-method to get insights and verbatim behind the scores. The researcher could have conducted short, 30-minute interviews with participants after collecting the initial quantitative data, however this was eventually dismissed for two reasons.

1). Due to current macroeconomic pandemic conditions, the technology industry has been at the forefront of supporting organisations adopt technology, this has but a fundamental strain on sales executives and therefore obtaining an extra 30 mins commitment of participants time would have been very challenging.

2). Fundamentally, for this research it was not needed, the three research questions and the hypotheses could be analysed and discussed with a quantitative data collection method.

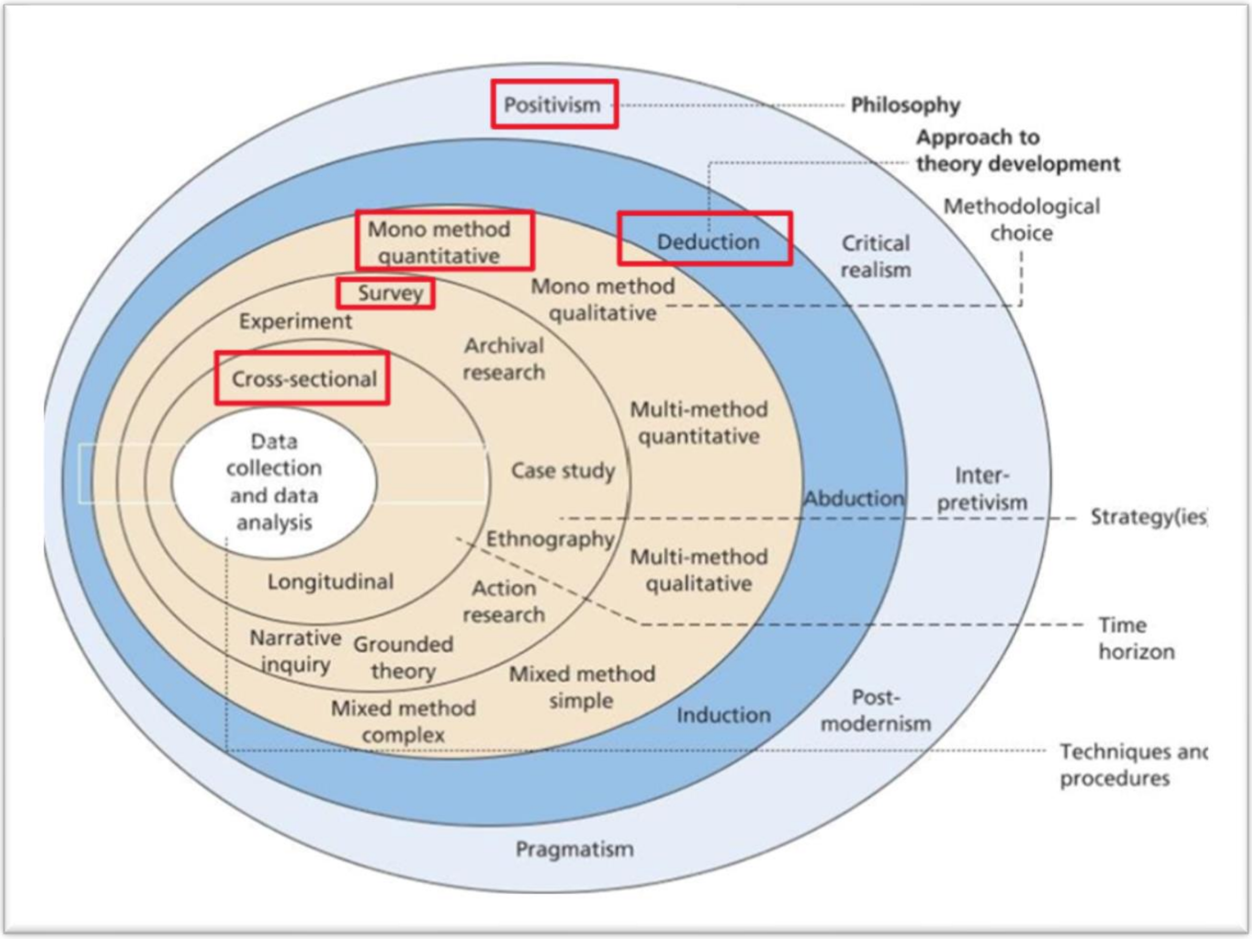

Figure 4: Research Onion, Saunders et al, 2012.

3.6 Mode of Data Collection

As a means to collect primary data, the author compared many ways of collecting data and concluded the best method would be through a self-completed internet questionnaire, which could be completed via mobile or on a desktop depending on the preference of the participant. It was ruled out at an early stage to use secondary sources due to the limited research publications in this area. A quantitative data collection through an online survey was chosen as the best form of data collection. The short time needed to administer the survey was a key factor in the researcher's decision. The survey was constructed on Microsoft Forms and consisted of 14 questions. Microsoft Forms was chosen as the questionnaire platform due to the security and compliance parameters. The researcher was able to pseudonymise the data of the participants using active directory controls. In addition, restrictions were put in place so that external users could not complete the survey and the survey could only be completed once by each participant.

A strict time was set from 22nd June to the 3rd of July to collect the data. The aim was to get a sample size of 50 sellers and analyse the data. The method of communication was an email to managers and supervisors requesting they ask their teams to fill out the survey. In addition, individuals were also emailed. There was one reminder email that went out on Monday 29th June and individual messages to participants through a unified communications tool (Microsoft Teams).

3.7 Ethical considerations

The data collected for the purpose of this research does not contain any sensitive or personal identifiable information in relation to the respondents who participated in the survey. All participants were informed that it was an anonymous survey and controls were put in place to pseudonymise the email domains of the participants. Each participant required an email domain from the company that was surveyed to gain access. This control was put in place to limit each participant to completing the survey once only, and in addition limit the external sharing so it could not be completed by anyone outside of the organisation. This method was adopted in line with the positivism research philosophy to purely understand any data correlations between variables. In addition, by not generating any PII data, the researcher has kept in accordance with all data regulations such as GDPR and ISO2007. All data subjects were over the age of 18 and understood the data collected will not be identifiable to them.

3.8 Validity and reliability

Missing data from quantitative questionnaires is common (Quinlan, 2011). Sometimes participants will not answer every question, or some questions might not be applicable. To counter this, the author made every question asked mandatory, participators could not submit results without answering every question. By doing so there were no missing data points and therefore no need to factor in additional coding within SPSS for non-responses. There are pre-existing validated questionnaires in relation to salesforce adoption, however, there is a limited research for the impact of AI in sales. Therefore, this research required designing a questionnaire adapted from previous salesforce automation surveys as discussed in the survey structure.

The Cronbach's Alpha test calculates correlations between variables: the stronger the correlation the higher the data validity (Heale & Twycross, 2015). The calculation is a widely accepted reliability test for quantitative research and applies particularly favourable for Likert scales. The researcher designed a questionnaire with 14 items – the structure is discussed further below. The data obtained under numerical variables (8 out of 14 variables) gave a result of 0.461 on the Cronbach's Alpha test confirming that the questionnaire is valid and reliable in the format presented.

Reliability Statistics	
Cronbach's Alpha	N of Items
.461	8

Case Processing Summary			
		N	%
Cases	Valid	41	100.0
	Excluded[a]	0	.0
	Total	41	100.0
a. Listwise deletion based on all variables in the procedure.			

3.9 Research Population & Sample

For this research, the target population size for the survey consisted of 300 sales professionals employed at the same multinational organisation. It was important to target the sales roles that used the lead recommender tool and did not include support or engineering roles, as discussed in the methodology. Quinlan (2011) suggests that a quantitative research study should consist of a large sample population, as a result the researcher aimed to get as many surveys completed from the sample size in the targeted roles.

The aim of the researcher was to get over 60 responses from the 300 sales executives asked to participate. The total respondents and sample for this research was 41. Although the desired target quantity was not met, there are still valuable insights gained which contributes to the literature.

3.10 Questionnaire structure

The questionnaire was inspired and adapted from Homburg, Wieseke and Kuehnl's (2010) study of social influence on salespeople's adoption of sales technology. The structure consisted of three sections that contained multiple questions.

1. Role, time in sales and attitudes on adoption.
2. Perceived value.
3. Training.

The survey opens to gain insight into the sales executive's role, their sales tenure, and tool adoption attitude (questions 2-6). Perceived value (questions 7-11) aims to get insight into how the tool assists each participant to increase pipeline revenue and enhance customer engagements. The survey concludes by asking about the training experience (questions 11-14).

Contrasting data from each section will give the researcher a view of trends and significant correlations. Rensis Likert developed the widely used Likert Scale, with its purpose being to measure the direction and force of attitudes (Quinlan, 2011). A Likert Scale can be either a 3-point, 5-point or 7-point scale. The structure of the survey leverages this to understand the attitudes of the participants towards the lead recommender tool. Eight of the questions use a 5-point scale, as the more points to the scale, the more insight can be gathered in terms of attitudes held. The items are presented in Appendix A. The author developed a coding key to analyse the data from those questions as shown below.

Question number	Variable Name	Variable Description	Variable Labels
7	The usage of Lead Recommender tool in our digital sales environment enhances customer/seller engagement	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
8	The usage of Lead Recommender in our digital sales environment increases net new revenue pipeline.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
9	The usage of Lead Recommender in our digital sales environment enhances customer satisfaction.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
10	The usage of Lead Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
11	The usage of Lead Recommender in our digital sales environment increases the stress in my work.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1

12	In relation to training and support for Lead Recommender, I was provided with detailed training.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
13	In relation to training and support for Lead Recommender, I was regularly provided with advice and tips for its usage.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1
14	In relation to training and support for Lead Recommender, there has been the possibility to receive adequate support if required.	○ Strongly agree ○ Agree ○ Slightly agree ○ Slightly disagree ○ Disagree ○ Strongly disagree	○ 6 ○ 5 ○ 4 ○ 3 ○ 2 ○ 1

3.11 Conclusion

In line with the previous literature, the author has used a logical and practical survey questionnaire to collect primary data to answer the research questions. A quantitative cross-sectional, mono-method gave the researcher the data required to analyse accordingly, whilst keeping to the time parameters set. Other methods were considered however they were eventually dismissed due to timing and the current macro-economic and pandemic factors. The research's decision to anonymise all the data and give the participants the opportunity to not continue with the questionnaire at any point, made it conducive in relation to ethical considerations.

Chapter 4: Findings & Discussion

4.1 Introduction

The author has used Exploratory Data Analysis (EDA) as the initial phase to present the data. Tukey (1961) defined data analysis as "procedures for analysing data, techniques for interpreting the results of such procedures, ways of planning the gathering of data to make its analysis easier, more precise or more accurate, and all the machinery and results of (mathematical) statistics which apply to analysing data".

The collection of data was exported from Microsoft Forms as a Microsoft excel file, then imported onto IBM's Statistical Package for Social Science (SPSS) tool as described below. Once imported into SPSS, the author was able start unpacking the data and discuss the relevant findings. The EDA approach emphasises the use of graphs and visuals to explore and understand the data. In the analysis section below, the author hopes to offer the reader simple visualisations that help to articulate the findings. The data analysis has been structured in three headings (4.4.1, 4.4.2 & 4.4.3) in accordance with the three hypotheses and concludes on a discussion regarding the research limitations.

4.2 Response Rate

The research consists of responses from 41 participants: 17 account executives, 3 demand response executives and 21 solution specialists (*figure 5*). A total population size of 300 employees that reside in the three targeted roles gives a sample percentage of 13%. The average completion time for the survey was 15.08 minutes and most responses were completed in the first week of the go-live date (22nd June – 28th June). A reminder to complete the survey went out to potential participants on the first day of the second week (29th June) of which yielded and additional 5 survey completions. This concluded the 2-week window to collect the data and the response trend suggests that participants were more inclined to complete the survey on the initial prompt.

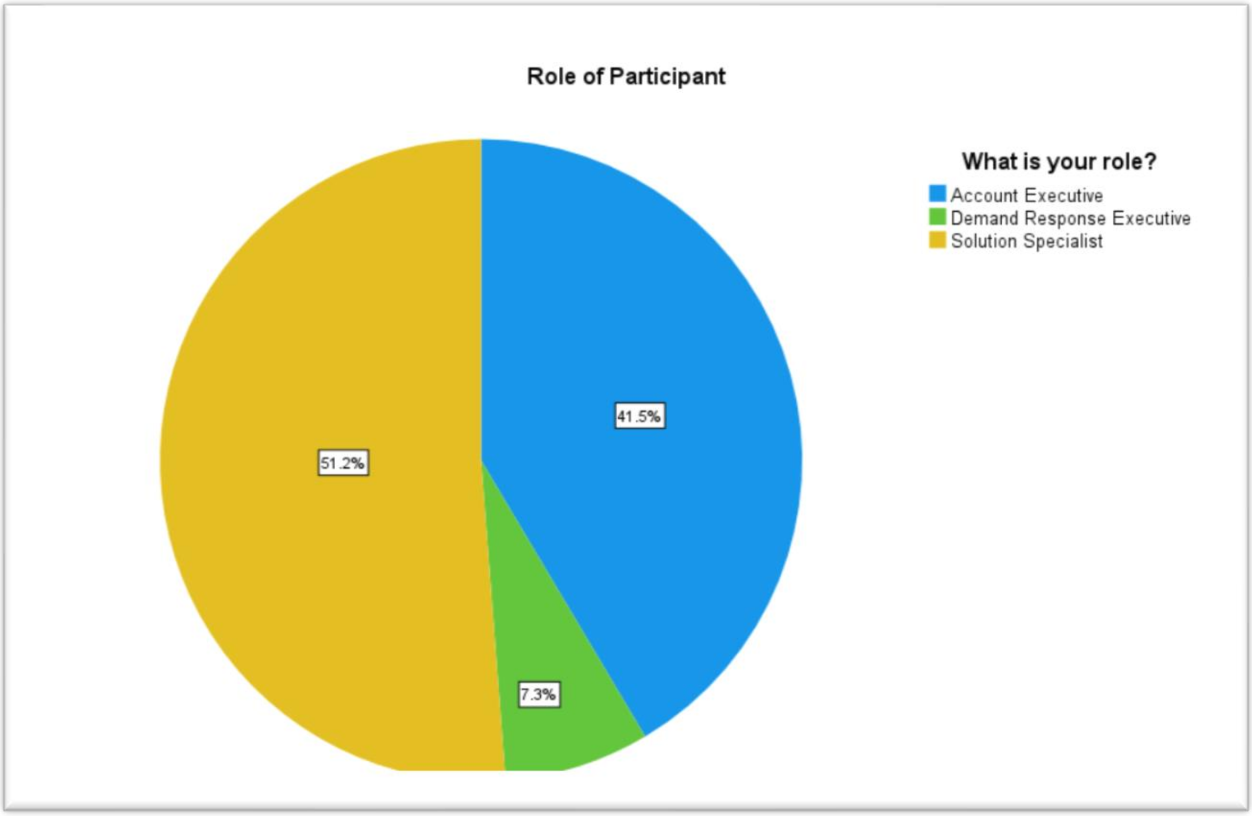

Figure 5: Role of Participant

4.3 SPSS

The primary quantitative data was collected through Microsoft forms, imported into IBM SPSS and analysed accordingly. IBM SPSS Statistics is software that can be used for batched or interactive statistical analysis. The tool was pivotal in organising, correlating, and presenting the data, for the author to gain relevant insight and outline the discussion. The tool is highly regarded by research scholars and has been widely used to analyse statistical data over the last 50+ years. The easy-to-use interface and automated Graphboard template designs weighed heavily on the research's decision to use the tool.

4.4 Data Analysis

The data collected from this research is quantitative in nature and required statistical analysis. There are some interesting discussion points that support and do not support the three hypotheses.

4.4.1 H_1 Attitudes & adoption with perceived usefulness

Hypothesis 1 (H_1).

> The higher the lead recommender tool adoption rate, the higher the perceived usefulness will be.

White-collar sales executives are some of the most technophobic and resistant to change (Mills, 1995), however, participants expressed favourable adoption and attitude towards the lead recommender tool. Question five and six were the key variables to ascertain participants adoption and behaviours in relation to the tool. *Figure 6* shows the results of the participants 'best description' towards the lead recommender tool. There were five options for participants to choose from (see question 5, Appendix A) and no participants chose "I do not use the tool since I am afraid of making a mistake during my operations" - only one participant (2.4%) does not benefit from using the tool. This would suggest that participants are using the tool and 31.7% will use it as often as possible. These data points will be discussed again when looking at the level of training offered to get these favourable adoption behaviours.

How would you best describe your behaviour in relation to adoption?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	I use the tool as often as possible	13	31.7	31.7	31.7
	I use the tool most often in my operations	10	24.4	24.4	56.1
	I use the tool rather seldom compared with other tools	17	41.5	41.5	97.6
	I do not use the tool since I cannot benefit from it's usage	1	2.4	2.4	100.0
	Total	41	100.0	100.0	

Figure 6: Adoption Table Results

Figure 7 is a histogram copied from SPSS that shows the data from question six (my personal attitude concerning the tool). In line with the adoption behaviours above, the data suggests there is a consensus of positivity towards using the AI tool. Twenty-seven participants (65.8%) gave a favourability rating of five or above. Homburg et al. (2010) conducted a multilevel analysis on SFA adoption that measured the same construct. A survey of 1,040 salespeople measured their personal attitude in relation to the new SFA tool (using a Likert scale, 1- unfavourable, 7- favourable). The mean and SD results are extremely harmonious. Despite the research being a decade apart, there are similar attitudes from salespeople in relation to SFA tools.

Study	Salespeople	Mean	Standard Deviation
Homberg et al (2010)	1,040	4.89	1.38
Current Paper	41	4.98	1.458

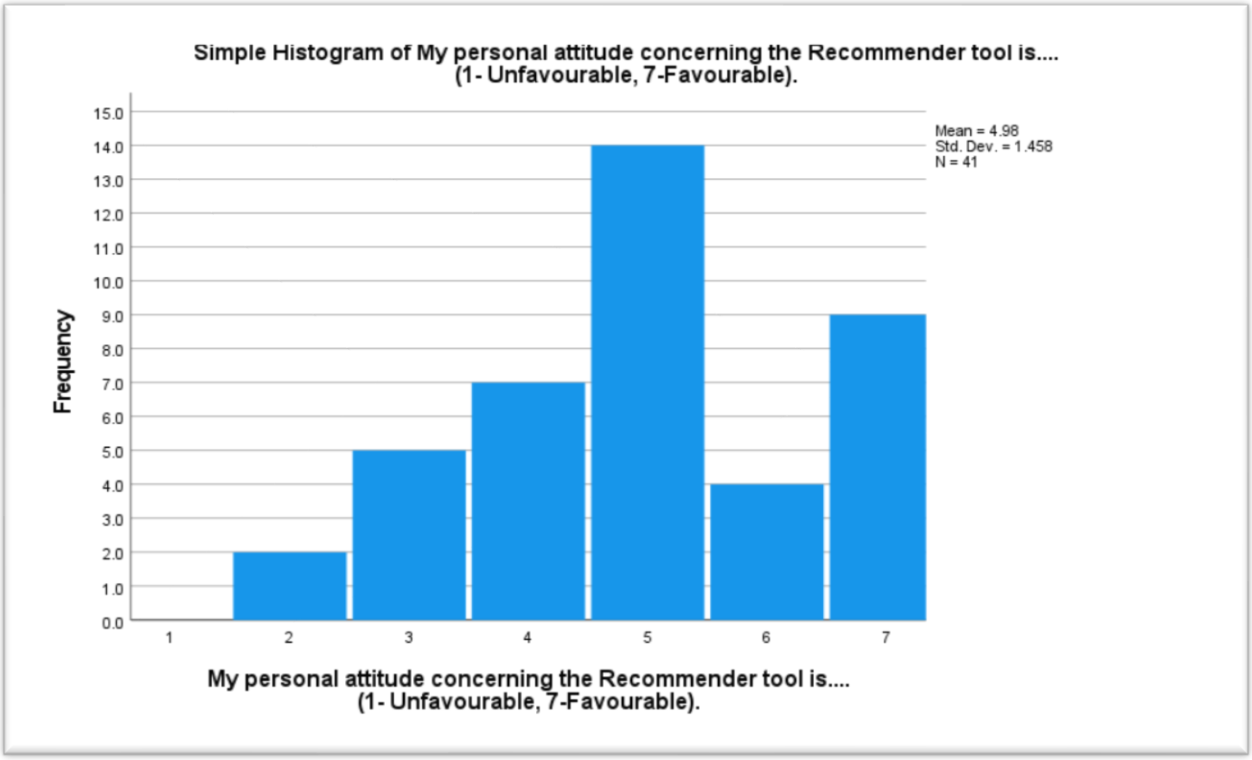

Figure 7: Histogram of Attitudes

From these data points, the researcher has concluded that both the adoption and attitudes towards the lead recommender to are favourable, therefore, in line with H1, this should equate to a higher perceived value and usefulness.

To unpack this, the author has taken data points from the questions relating to perceived value and perceived usefulness (question seven, eight, nine & ten). *Figures 8, 9, 10 and 11* show histograms of the results from these four questions. The graphs are very similar to one another and closely mimic the attitudes towards the tool.

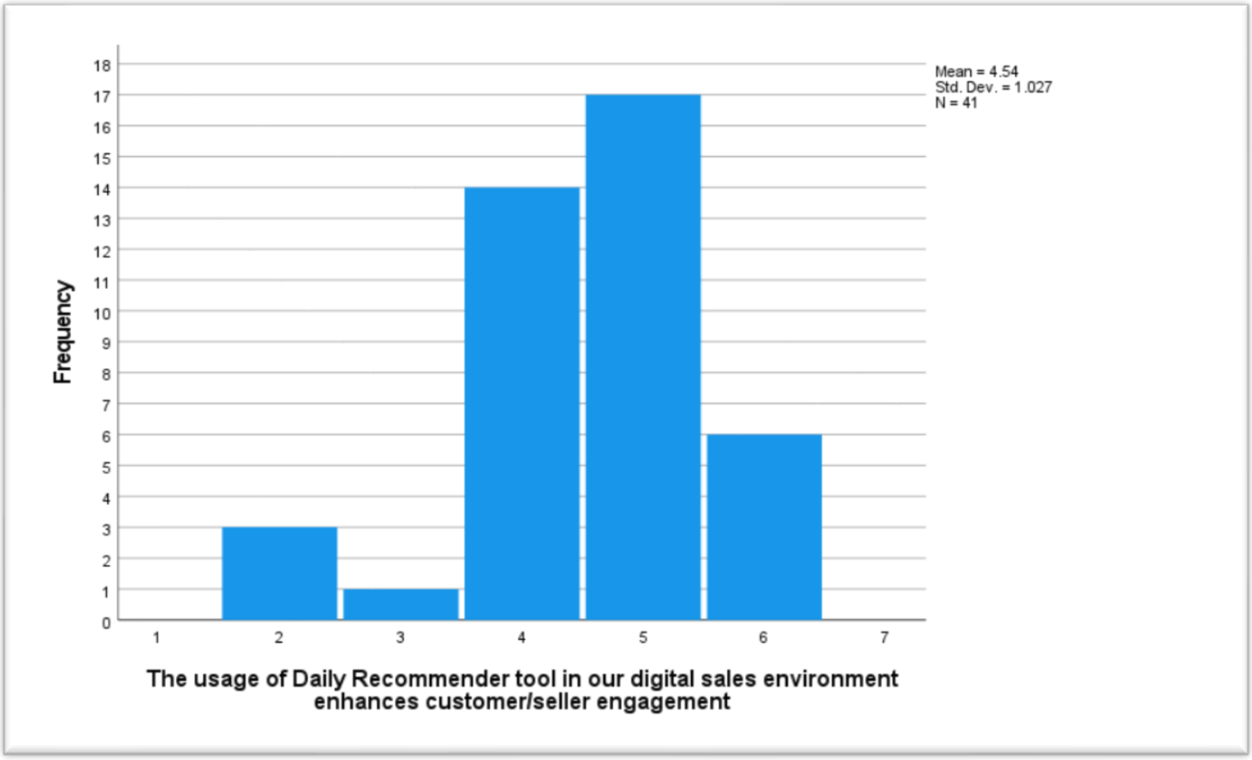

Figure 8: Histogram. Usage and enhanced customer/seller engagement

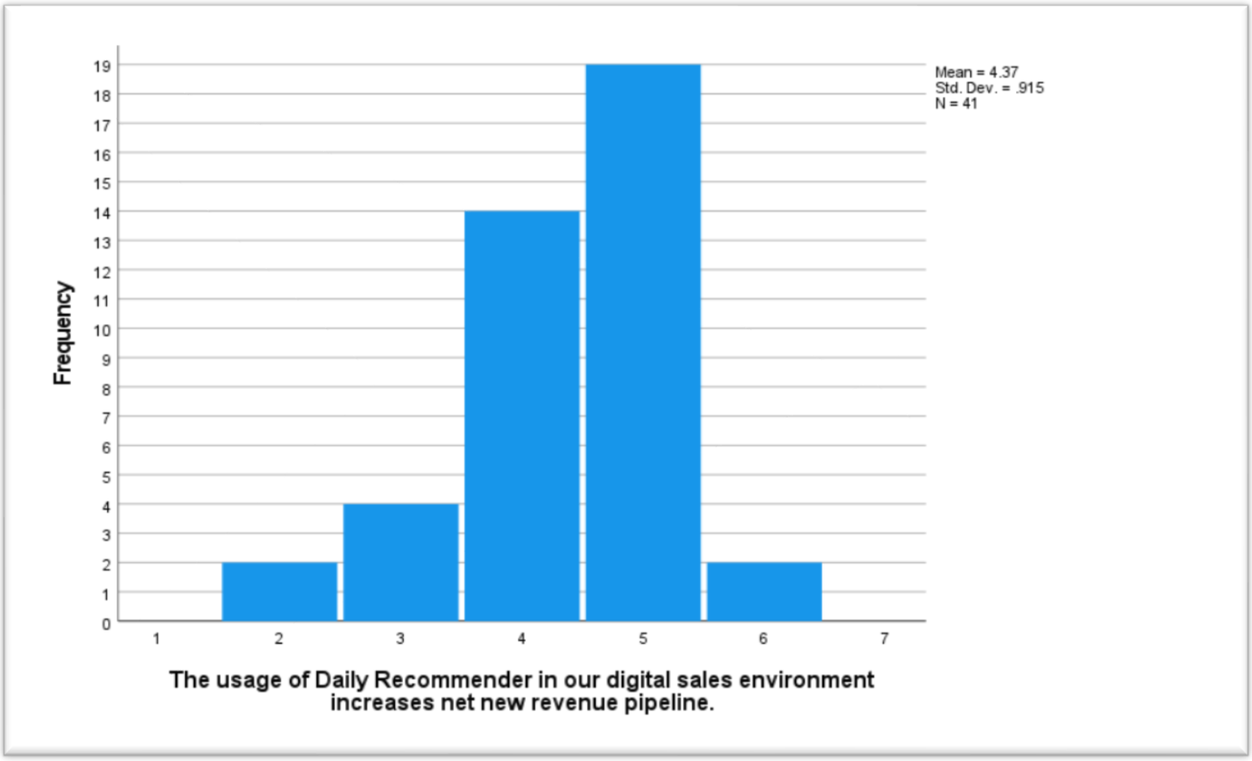

Figure 9: Histogram. Usage and increased net new revenue pipeline

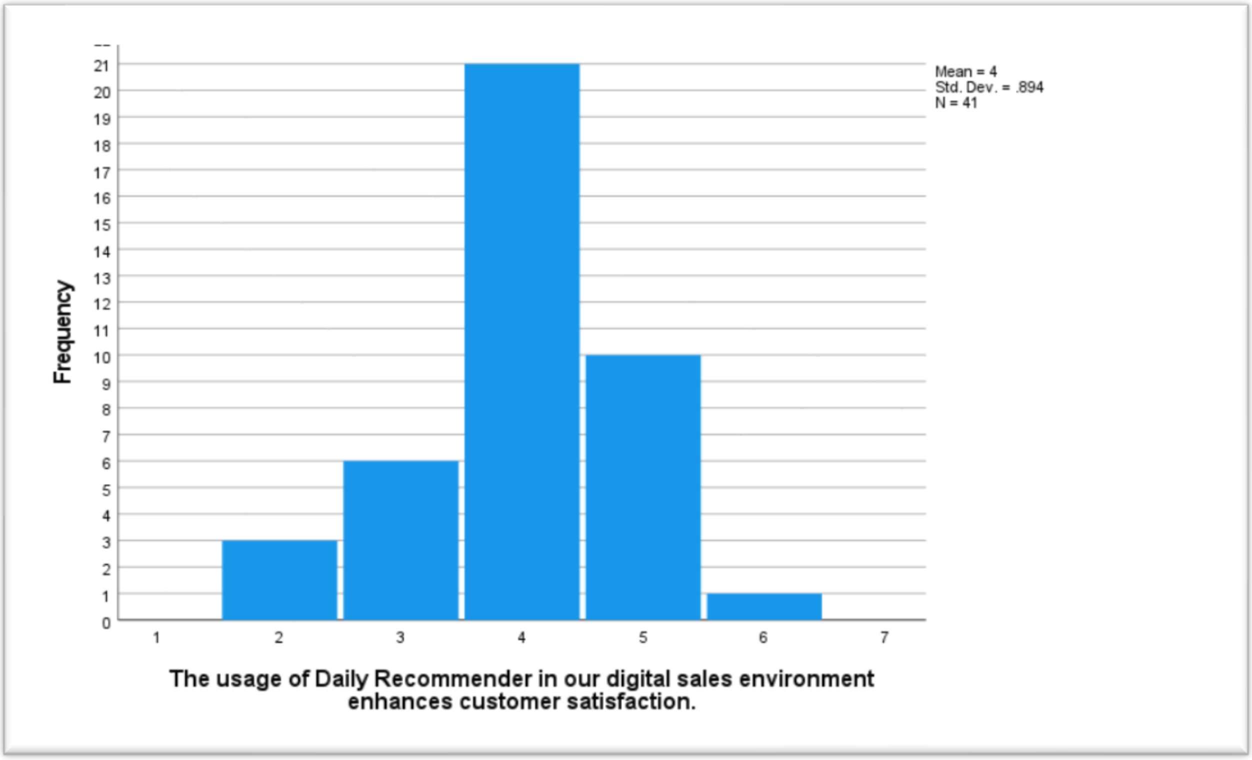

Figure 10: Histogram. Usage and enhanced customer satisfaction

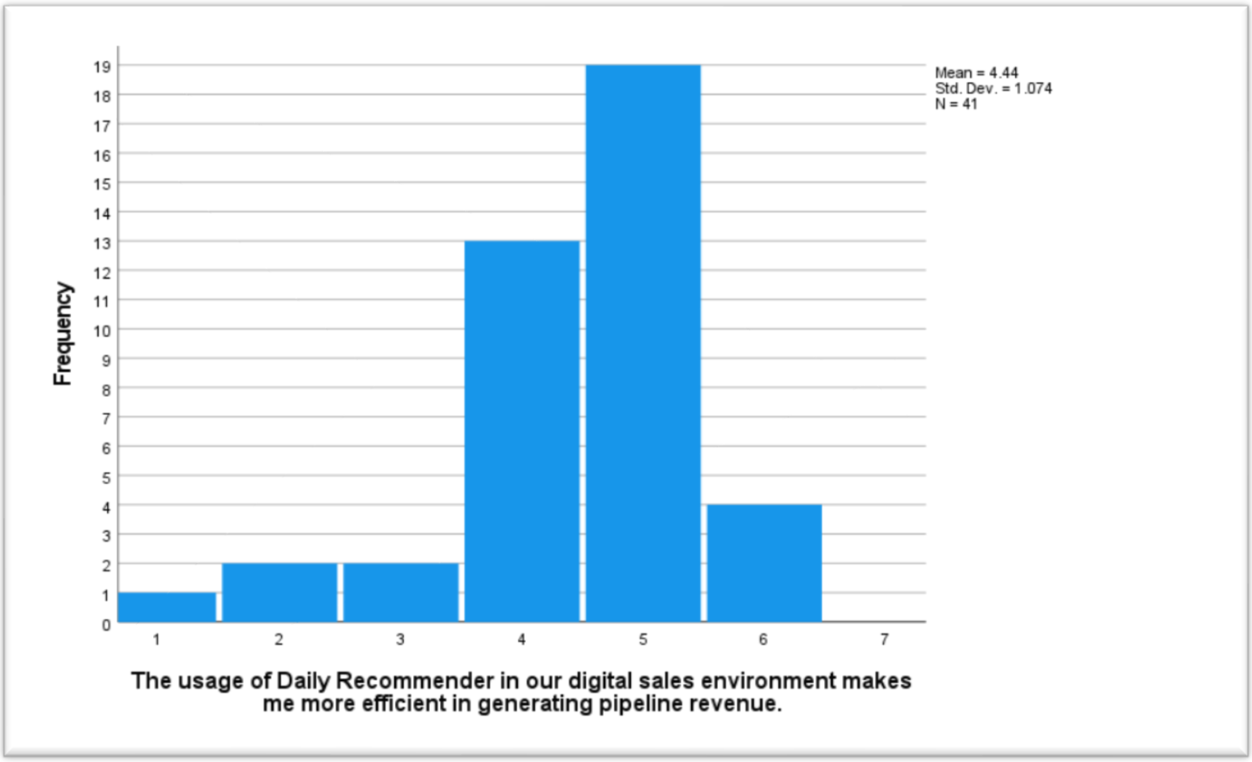

Figure 11: Histogram. Usage and pipeline generation efficiency

These data points show that participants accept that more favourably than not, the tool does help them to generate revenue and enhance the customer service, thus suggest that there is a perceived value.

Coupling this with the data from the perceived value questions, the research has identified that there is a significant correlation between behaviour & usage and pipeline generation & customer engagement as depicted in *figure 12.*

Correlations

		The usage of Daily Recommender in our digital sales environment increases net new revenue pipeline.	How would you best describe your behaviour in relation to adoption?	The usage of Daily Recommender tool in our digital sales environment enhances customer/seller engagement	The usage of Daily Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.
The usage of Daily Recommender in our digital sales environment increases net new revenue pipeline.	Pearson Correlation	1	-.576**	.743**	.570**
	Sig. (2-tailed)		.000	.000	.000
	N	41	41	41	41
How would you best describe your behaviour in relation to adoption?	Pearson Correlation	-.576**	1	-.461**	-.375*
	Sig. (2-tailed)	.000		.002	.016
	N	41	41	41	41
The usage of Daily Recommender tool in our digital sales environment enhances customer/seller engagement	Pearson Correlation	.743**	-.461**	1	.711**
	Sig. (2-tailed)	.000	.002		.000
	N	41	41	41	41
The usage of Daily Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.	Pearson Correlation	.570**	-.375*	.711**	1
	Sig. (2-tailed)	.000	.016	.000	
	N	41	41	41	41

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 12. Correlations between variables

From this analysis, the researcher can conclude that the data supports H_1 - the higher the lead recommender tool adoption, the higher the perceived usefulness will be.

4.4.2 H_2 Sales experience and SFA adoption

<u>Hypothesis 2 (H_2).</u>

> The more experience of a sales professional, the perceived value of Lead Recommender will not be as high.

In line with H_2, scholars have observed and concluded that more experienced sales professionals are less likely to adopt new sales technology (Hunter and Perreault, 2006). However, the data collected in this study suggests that tenured sales professionals within the company have embraced using AI.

Among the twenty-two participants who have been in the sales function **for over five years**, **68%** responded with a tool favourability rating of 5-7 (*figure 13*). **90%** of participants that have been in a sales role for over five years answered **Strongly agree, Slightly agree or Agree** to question eight *(figure 14).* This was a key data point as generating net new revenue pipeline is associated to sales performance success, which supports the theme that tenured sales executives perceive the tool as useful and subsequently results in higher adoption.

Within the SPSS tool, the researcher analysed the participants that have been in a sales role for longer than five years. He was able to do this by splitting the file according to 'time in a sales role' and then adding the five variables relating to perceived usefulness. *Figures 14, 15, 16 & 17* show a histogram relating to the perceived usefulness variables and the data suggests a participants that have been in a sales role for more than five years see value in using the tool.

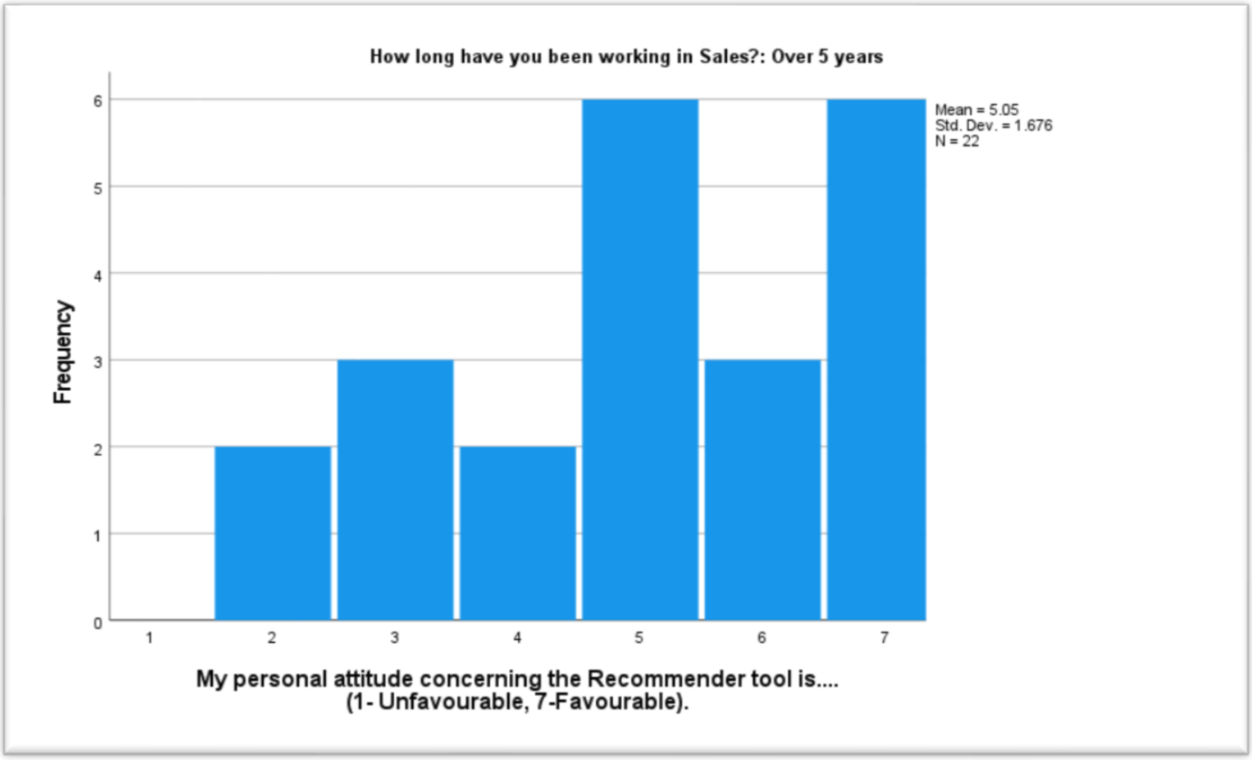

Figure 13: Histogram. Personal attitudes towards AI

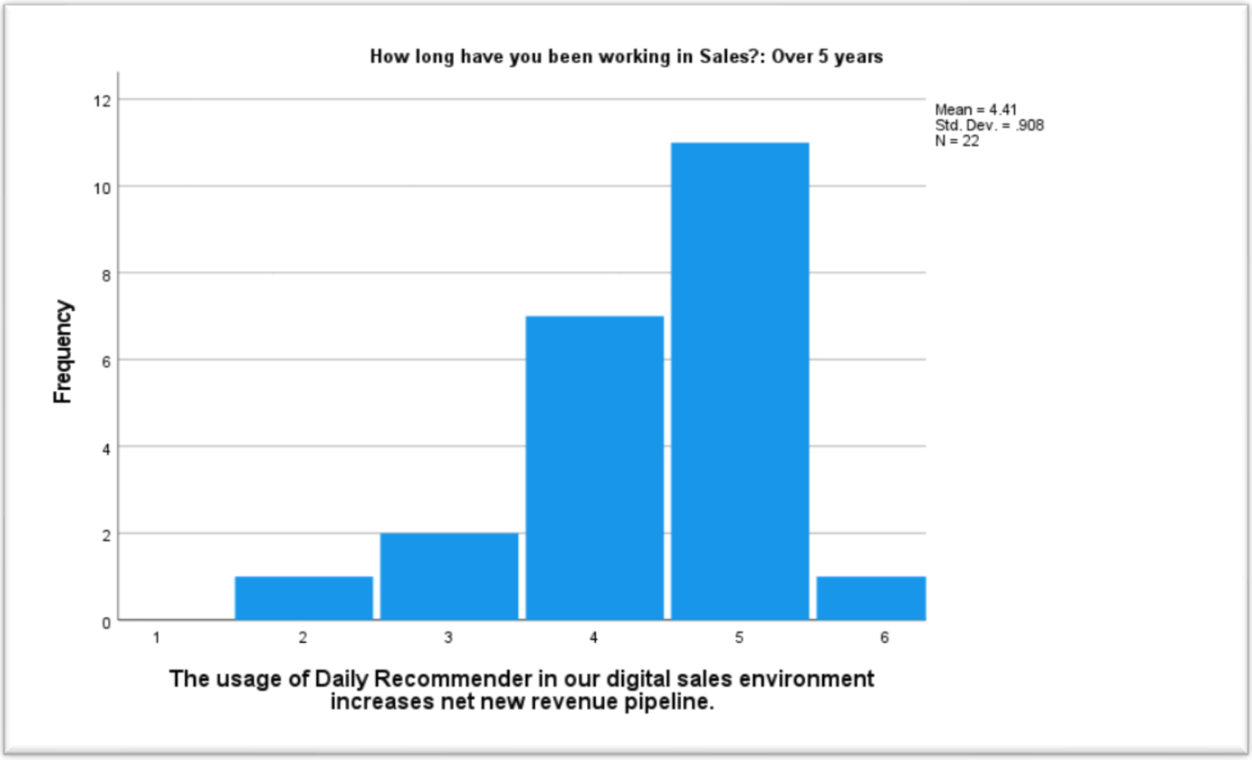

Figure 14: Histogram. Sales executives over 5 years and pipeline revenue increase

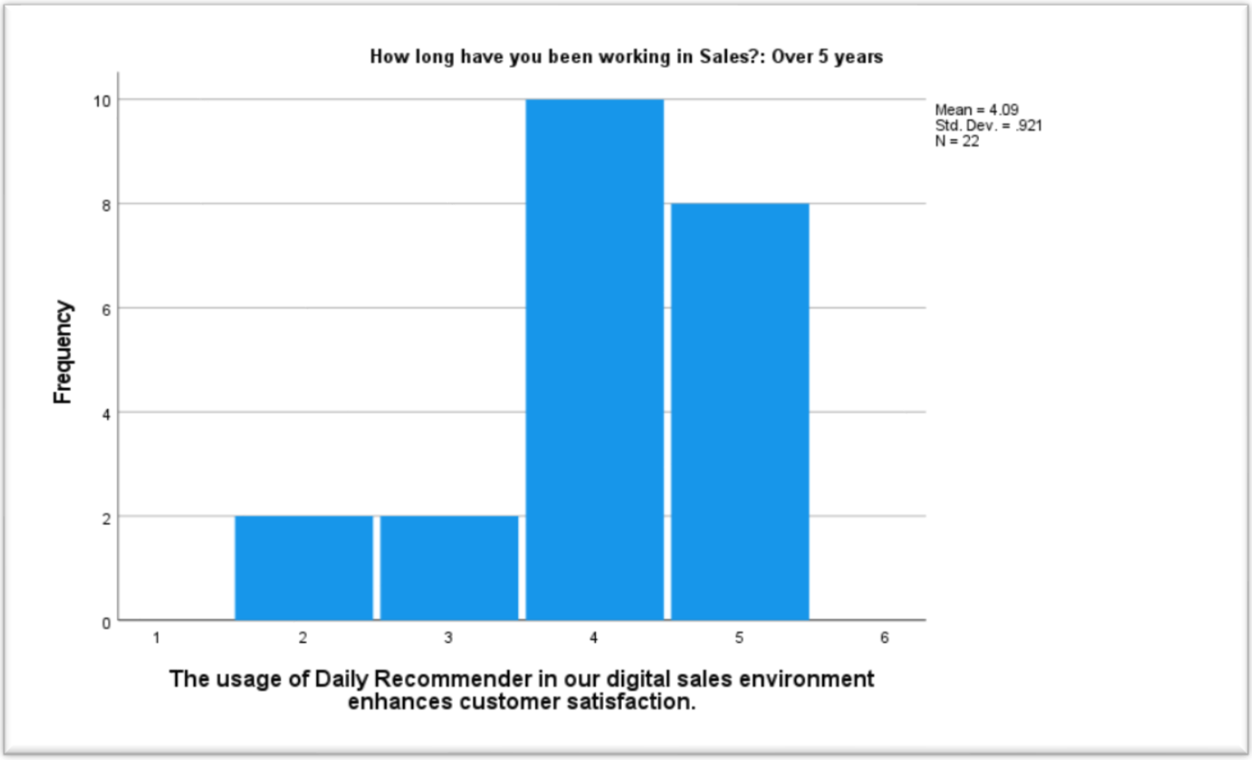

Figure 15: Histogram. Sales executives over 5 years and increased customer satisfaction

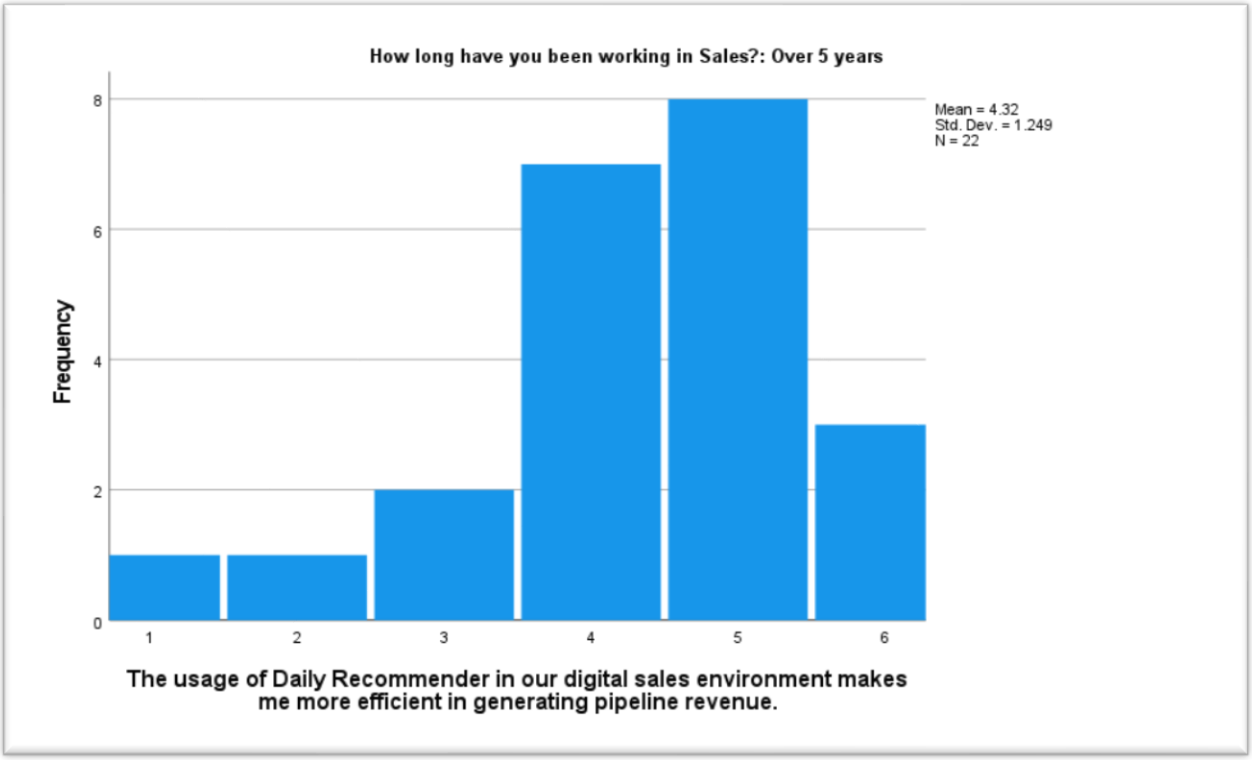

Figure 16: Histogram. Sales executives over 5 years and pipeline generation efficiency

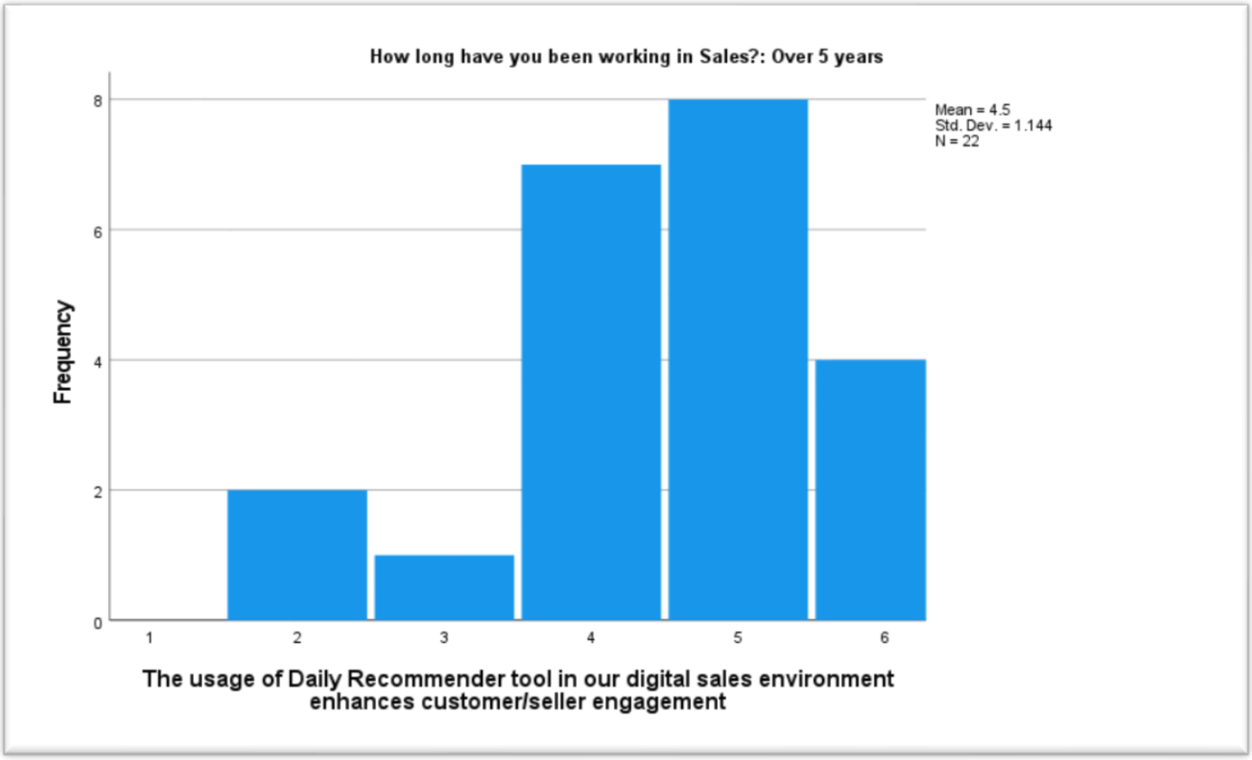

Figure 17: Histogram. Sales executives over 5 years and customer/seller engagement

In addition, an interesting data point is that even when participants' personal attitudes towards the tool are unfavourable (*figure 5*), which conveys a frequency of five, the data suggests that these participants still accept and acknowledge the tool does support in increasing revenue pipeline, thus perceiving the tool to be valuable. Moreover, *figure 18* shows a complete overview of the behaviour in relation to tool adoption for each sales experience category, only one from forty-one participants said they 'do not use the tool as they do not see benefit from its usage'. Thus, contributing to the conclusion that regardless of sales tenure, sales executives are benefiting from SFA adoption.

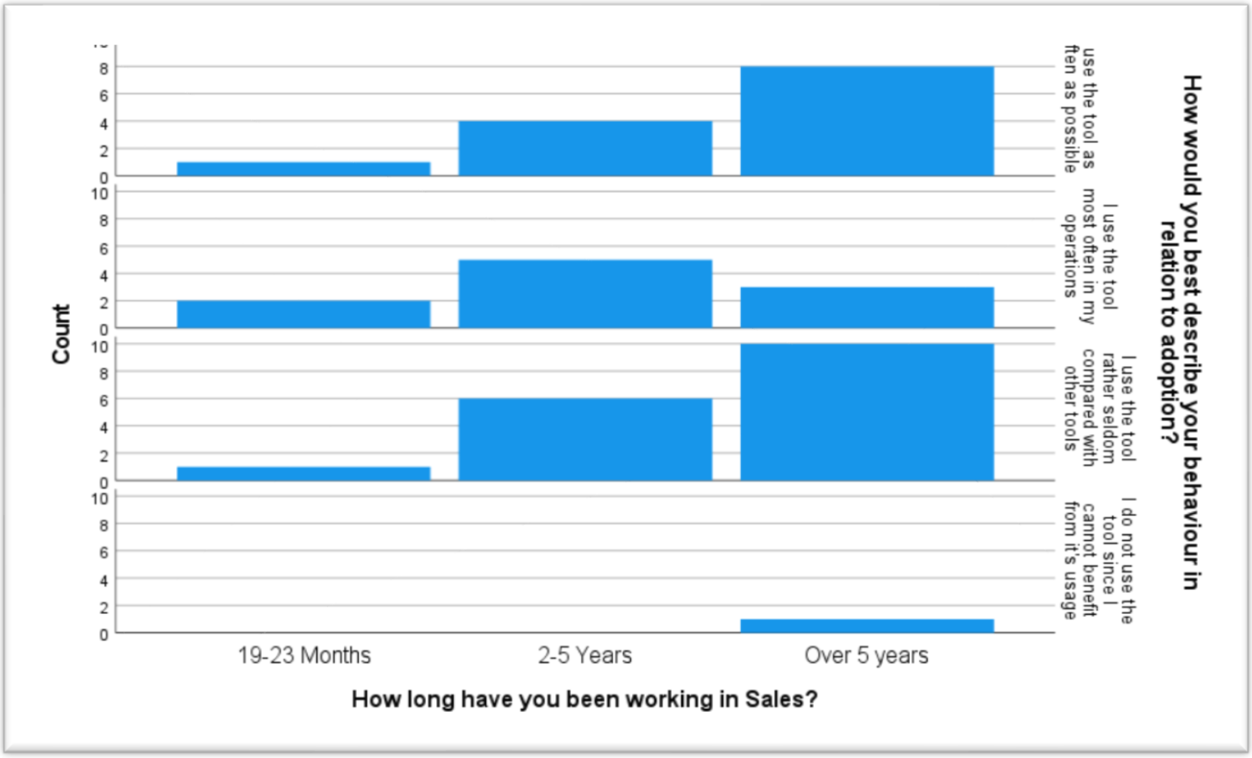

Figure 18: Split histogram. Behaviour in relation to AI adoption

The data from this part of the research contradicts the conclusions from (Hunter and Perreault, 2006). There is a clear view that shows, regardless of the sales experience, sales executives do perceive the lead recommender tool to be valuable and benefit from its adoption. However, one of the key limitations of this research (outlined in limitations) is its extensibility, it is a small quantitative survey across one organisation that in the technology industry. Therefore, sales executives may have a positive pre-disposition regarding technology adoption and future research could look to see if there are similar trends across other industries. In addition, the researcher acknowledges that the scale may not have been wide ranging. An additional category of over ten years in sales could have yielded a more accurate representation of the participant's sales experience. Lastly, coupling this quantitative data with qualitative verbatim would have given a more in-depth view on the participants perception to the tool's value, thus the researcher encourages future research to consist of the multi-method approach if time permits.

To conclude this section, the data is not consistent with the H_2. The researcher hypothesised that the longer the sales executive has been in a sales role, the less favourable the sales executive will perceive the tool to be. However, after analysing the data, sales executives across all experience level perceive the tool to be valuable and therefore sufficient adoption has occurred.

4.4.3 H_3 Training, adoption, and perceived value

<u>Hypothesis 3.</u>

> Sales executives with less training of the tool, will have a far lower adoption and therefore will have a negative view of its usefulness.

A global survey of 513 firms (CSO Insights 2019) reveals that sales training focusing on the sales process is critical for sales executives to improve adoption and improve deal win rates. The researcher analysed sales executives with a lesser amount of tool training and identify correlations with a lower SFA adoption behaviour and subsequently a diminished perceived value. Using SPSS, the researcher used training and support provided as the dependent variable.

The data suggests there was diverse mix of training and support offered to sales executives. Answers ranged from disagree to strongly agree when asked; In relation to training and support for Lead Recommender, I was provided with detailed training *(figure 19 & 20).* The mean for this question was 4.15, however to analyse the impact of training and adoption, the researcher chose to focus on the data points relating to inadequate training provided (participants that chose a two or three on the Likert scale).

In relation to training and support for Daily Recommender, I was provided with detailed training.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Disagree	6	14.6	14.6	14.6
	Slightly disagree	5	12.2	12.2	26.8
	Slightly agree	12	29.3	29.3	56.1
	Agree	13	31.7	31.7	87.8
	Strongly agree	5	12.2	12.2	100.0
	Total	41	100.0	100.0	

Figure 19: Frequency data for training of AI tool

Figure 20: Histogram of frequency for training and support for AI tool

In accordance with the researcher's H3 and based on previous literature (Homberg et al, 2010), the eleven participants (26.8%) that felt they did not have adequate training or support in relation to the tool, should equate to not having favourable personal attitude with the lead recommender tool. However, results show this is not the case, with the attitudes levels all being above four depicted in red in *figure 21.*

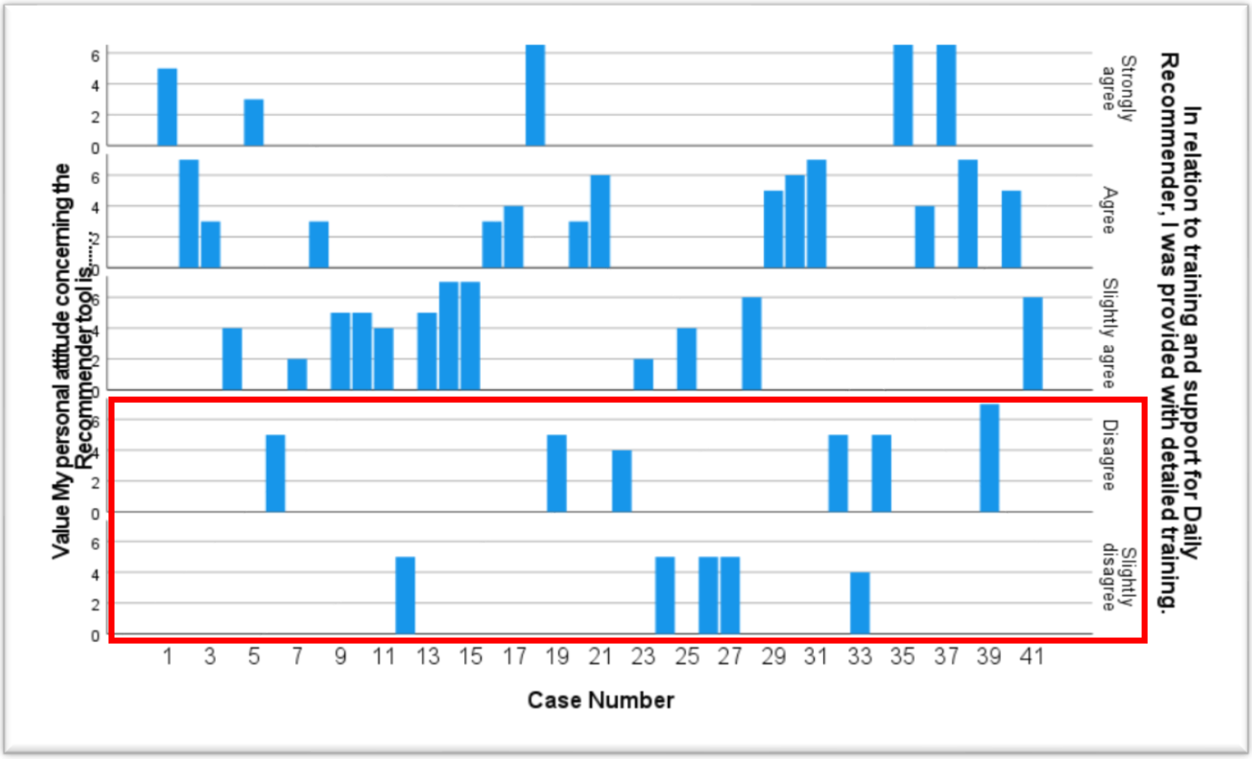

Figure 21: Histogram. Personal attitude and training.

This data point would suggest that regardless of the level of training, it doesn't not affect the personal attitude to using the tool and therefore would refutes H3. In addition, of the eleven participants that didn't receive adequate training, **93%** responded **Slightly agree or Agree** for question *8 (The usage of the Lead Recommender tool in our digital sales environment increases net new revenue pipeline).* This means that only one participant doesn't perceive any value from the tool. This suggests that training is not necessarily required for the tool to be perceived as valuable, thus discounting hypothesis 3.

Academic research publications suggest that user training and support is a vital part for companies to have a successful SFA adoption and implementation (Ahearne et al. 2005; Jelinek et al. 2006; Jones et al. 2002). A study by Sarin et al. (2010) gives evidence supporting a salespersons ability to adopt SFA tools is positively impacted by the effectiveness of the training- in line with the salespersons learning orientation. The research conducted for this study suggests that sales executives did not require training for them to realise perceived value, however, extensive research in this area is required to look across industries, as sales executives in this field would be expected to have a basic understanding of technology value to improve organisation efficiencies.

4.4.4 SFA Adoption and stress

Research around change in sales operations or the introduction of new SFA tools has contributed to the conclusion that stress can have a negative effect on adoption (Cheng, Bao, Zarifis, 2020; Rangarajan et al, 2005). Although this was not a prominent area for this research, the data in relation to question eleven in the survey suggests that 56% of participants did not believe the tool adds stress to their day-to-day work activities.

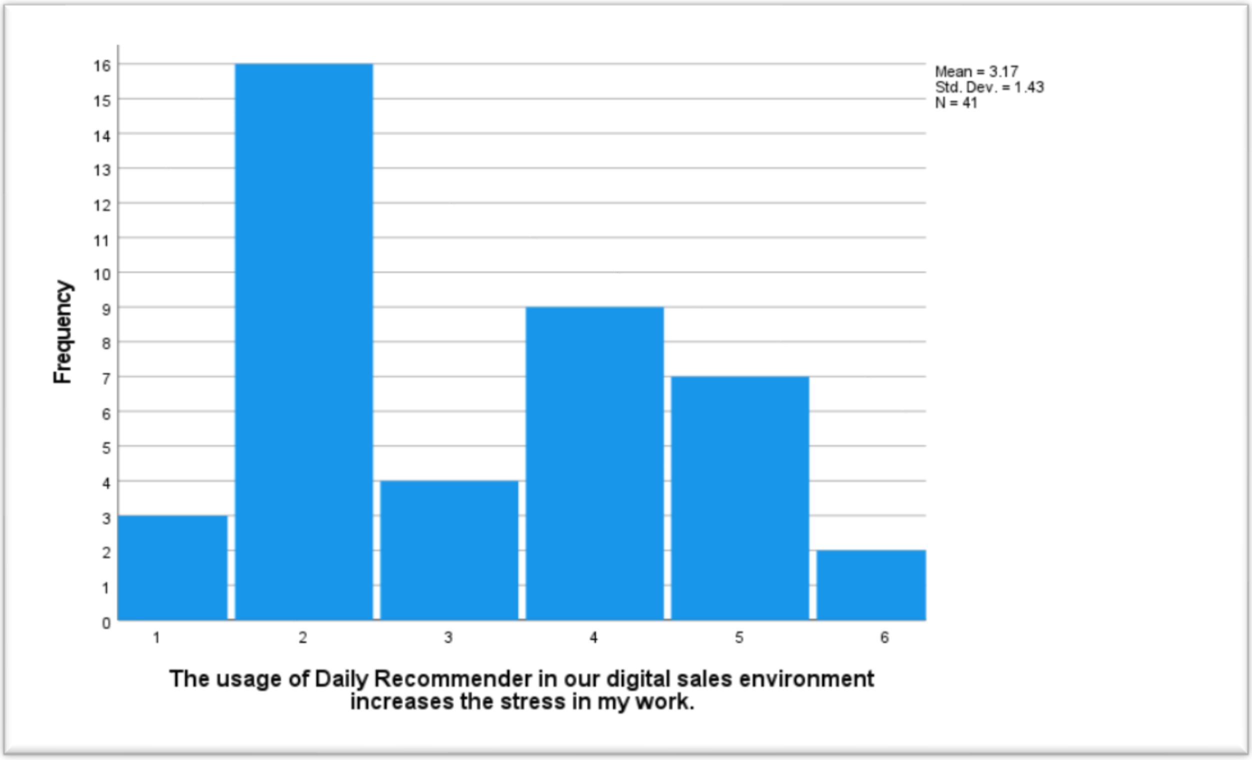

Figure 22: Histogram. Stress from using AI.

4.3 Research Limitations

This research has limitations and is by no means extensive. Specifically, the absence of official sales performance data does limit the AI's perceived usefulness to perceptual performance measures, therefore the perceived usefulness measures are all subjective. The researcher did not have access to individual sales figures because the use of such data was precluded by the organisation in which the study was conducted.

In addition, of a population size of 300 potential participants, the researcher collected 41 completed surveys, therefore a small delta in the participants to role ratio. For example, the researcher could only get three demand response executives to complete the survey and therefore lacking an accurate representation from sales executives in that role. Moreover, while using one quantitative approach to complete a dissertation is widely accepted as being sufficient (Horn, 2009), the research could have been more impactful if the author had adopted a multi-layered data collection design and conducted semi-structured interviews to collect qualitative data. This multi-layered approach may have given further insight into the levels of training offered and verbatim for the tool's perceived usefulness. However, due to the global COVID pandemic affecting the current business, the was not enough time allocated to collect this additional data.

The research was conducted as a cross-sectional survey within one company. By working with one company, the author was able to control for extraneous effects, however, for future research it maybe be valid to included multiple companies across an industry to gain more generalizable results. Moreover, when measuring the impact of SFA adoption in relation to training provided, it would be remiss not to draw attention to the industry of the organisation, the research was conducted in a leading multinational technology company, therefore the IT literacy will naturally be higher than other sales executives in different industries. Finally, the scale for tenure in sales was limited. No participant was in sales for less than three years and the author did not put an option for over 10 years, which could have been relevant.

4.4 Suggestions for further research

This research has identified useful insights, however it was in the context of a single company research approach, therefore, from the view of generalizability, future research could be conducted to investigate across-company variation. Future research should incorporate multiple organisations across different industries to further expand on the impact of AI in sales. In addition, the author wanted to limit the amount of personal identifiable information collected and therefore this study did not collect the gender of each participant. Venkatesh & Morris (2000) conducted a study around SFA which concluded women's SFA was more influenced by perceptions of ease of use and Men were more influenced by perceptions of usefulness, although the effect of subjective norms diminished over time – crossed gender analysis research in this area could be further explored as more companies look to adopt more AI tools across the business functions.

Another area which could spark a fruitful discussion would be to examine the impact of AI in sales from a managerial or sales leadership perspective. For example, how is hiring impacted with the use of AI being a prominent tool in the sales function, would sales managers require future candidates to have a high level of "machine intelligence". In addition, what impact would this have in relation to sales training and retaining talent. As a result of SFA tools being implemented, will staff need regular training and adoption programs and therefore potentially impacting the sales culture. Moreover, with the productivity gains from implementing SFA tools, what can the sales team improve upon with the additional time saved.

To the authors knowledge, there is limited up-to-date research around the how implementing individual key performance indicators (KPI's) can support adoption of SFA tools. Parthasarathy & Sohi (1997) classify the key factors of SFA adoption into three groups. "(1) nonmonetary costs of adoption; (2) personal, demographic and environmental factors; and (3) interpersonal communication". This paper offered a strong foundation for recent SFA adoption publications but does not consider the direct effect of sales managers and sales leaders directly implementing a metric to ensure adoption is effective.

Chapter 5: Conclusion

This research aimed to further understand the impact of AI within a digital sales environment, the author reviewed the literature and formulated three research questions in line with three hypotheses.

<u>1). Does AI have a positive perceived impact in a digital sales environment?</u>

The principal theme is sales executives are adopting the AI tool within the organisation where the research was conducted. According to previous literature, SFA adoption theorises that high adoption rates are associated with ease of use and perceived value. The data from this study suggests that the sales executives perceive the tool as an asset to generate revenue and enhance customer experience, thus improving sales performance. Therefore, can conclude that AI is having a positive impact within the sales function in a digital sales environment.

<u>2). Will the adoption of AI tools be negatively impacted by sales tenure?</u>

The data from this research suggests tenured sales executives see value with the tool and are adopting in a positive manner - directly negating H_2. However, as discussed in the research limitations, this could have been more thoroughly investigated by using a wider scaling metric, for example, analysing data from sales executives over 10 years' experience.

<u>3). Does training influence the perceived usefulness of AI and adoption?</u>

Although previous literature (Ahearne, Jelinek and Rapp, 2005) gives reveals SFA adoption will be negatively fundamentally impacted by inadequate training, the data from this study provides evidence to suggest that it is not required. In addition, the research was conducted within a technology company, therefore we must assume there is a level of technology literacy and therefore SFA adoption rates will be naturally higher.

There is an overwhelming amount of statistics across the industry offering evidence that AI development will have a continuing profound impact on all busines functions across the B2B and B2C environment. Large tech firms and interested parties are financially supporting research to contribute to the narrative of cost reductions and improved operational efficiencies gains from implementing AI technologies – McKinsey Global Institute (2017) estimated that private equity firms invested over $1 billion and venture capitalists invested over $4 billion to $5 billion in AI in 2016.

Technology continues to impact organisations globally and the recent pandemic has also accelerated digital transformation and technology adoption. In the context of market capitalization, seven of the ten top ten companies in the world are technology companies and there is now evidence to suggest that data is becoming the most valuable resource. Oil for centuries has been the dominant resource for society - whoever controlled the oil, controlled the economy. However, in today's economy it can be argued that data is more valuable because of the insight and knowledge that can be extracted and used. Governments and local data regulators have an obligation to make sure organisations are not abusing consumer privacy rights. Google acquiring Fitbit is being heavily scrutinised by EU regulators due to the sensitive nature of health data they'll have access to (Vincent, 2020). Microsoft’s decision to reject a deal with a Californian law enforcement agency is a shining example of how organisations and governments need to constantly ask the harder questions around AI implementation, it’s not necessary what AI can do, but what it should do. Microsoft concluded that by doing the deal “it would lead to innocent women and minorities being disproportionately held for questioning because the artificial intelligence has been trained on mostly white and male pictures” (Menn, 2019). Applying this to the sales function, organisations need to consider the bias effect when training the AI classifiers to make sure they are respecting the data privacy rights of the customer. The 2018 EU GDPR or general data protection regulation has updated controls that restricts cold calling and requires consent from participants to be contacted. In closing, the research is by no means extensive, however the author can conclude that there is a general theme of positivity to using artificial intelligence within a sales environment, and using AI tools will only add ammunition to a sales executive’s arsenal. In addition, if organisations do not look to adopt or invest, they could concede market share to competitors who are using AI tools. Future research in this area is encouraged to further understand the impact across the sales function and how data/knowledge/insights gives sales executives a competitive edge in the field.

“Now the reason the enlightened prince and the wise general conquer the enemy whenever they move, and their achievements surpass those of ordinary men, is foreknowledge” - Sun Tzu, The art of war.

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Appendices

<u>Appendix A- Questionnaire.</u>

Q1 Participant Consent
o I wish to participate in this research.
Q2 What is your role?
o Soltion Specialist
o Account Executive
o Demand Response Executive
Q3 How long have you been working in sales?
o 0-6 months
o 7-12 months
o 13-18 months
o 19-23 months
o 2-5 years
o Over 5 years
Q4 How long have you been working in Digital Sales at Microsoft?
o 0-6 months
o 7-12 months
o 13-18 months
o 19-23 months

○ Over 2 years
Q5 How would you best describe your behaviour in relation to adoption?
○ I use the tool as often as possible
○ I use the tool most often in my operations
○ I use the tool rather seldom compared with other tools
○ I do not use the tool since I cannot benefit from it's usage
○ I do not use the tool since I am afraid of making a mistake during my operations
Q6 My personal attitude concerning the Recommender tool is....(1- Unfavourable, 7-Favourable).
○ 1
○ 2
○ 3
○ 4
○ 5
○ 6
○ 7
Q7 The usage of Lead Recommender tool in our digital sales environment enhances customer/seller engagement
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q8 The usage of Lead Recommender in our digital sales environment increases net new revenue pipeline.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q9 The usage of Lead Recommender in our digital sales environment enhances customer satisfaction.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q10 The usage of Lead Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q11 The usage of Lead Recommender in our digital sales environment increases the stress in my work.
○ Strongly agree

○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q12 In relation to training and support for Lead Recommender, I was provided with detailed training.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q13 In relation to training and support for Lead Recommender, I was regularly provided with advice and tips for its usage.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree
Q14 In relation to training and support for Lead Recommender, there has been the possibility to receive adequate support if required.
○ Strongly agree
○ Agree
○ Slightly agree
○ Slightly disagree
○ Disagree
○ Strongly disagree

Appendix B- Codebook

What is your role

		Value	Count	Percent
Standard Attributes	Position	8		
	Label	What is your role?		
	Type	String		
	Format	A25		
	Measurement	Nominal		
	Role	Input		
Valid Values	Account Executive		17	41.5%
	Demand Response Executive		3	7.3%
	Solution Specialist		21	51.2%

How long have you been working in Sales

		Value	Count	Percent
Standard Attributes	Position	9		
	Label	How long have you been working in Sales?		
	Type	Numeric		
	Format	F12		
	Measurement	Scale		
	Role	Input		
N	Valid	41		
	Missing	0		
Central Tendency and Dispersion	Mean	5.44		
	Standard Deviation	.673		
	Percentile 25	5.00		
	Percentile 50	6.00		
	Percentile 75	6.00		
Labeled Values	1	0-6 months	0	0.0%
	2	7-12 months	0	0.0%
	3	13-18 months	0	0.0%
	4	19-23 months	4	9.8%
	5	2-5 years	15	36.6%
	6	Over 5 years	22	53.7%

How long have you been working in Digital Sales at

		Value	Count	Percent
Standard Attributes	Position	10		
	Label	How long have you been working in Digital Sales?		
	Type	String		
	Format	A12		
	Measurement	Nominal		
	Role	Input		
Valid Values	0-6 months		2	4.9%
	13-18 months		5	12.2%
	19-24 months		7	17.1%
	7-12 months		3	7.3%
	Over 2 years		24	58.5%

How would you best describe your behaviour in relation to adoption

		Value	Count	Percent
Standard Attributes	Position	11		
	Label	How would you best describe your behaviour in relation to adoption?		
	Type	String		
	Format	A60		
	Measurement	Nominal		
	Role	Input		
Valid Values	I do not use the tool since I cannot benefit from it's usage		1	2.4%
	I use the tool as often as possible		13	31.7%
	I use the tool most often in my operations		10	24.4%
	I use the tool rather seldom compared with other tools		17	41.5%

My personal attitude concerning the Recommender tool is.... 1Unfavourabl

		Value	Count	Percent
Standard Attributes	Position	12		
	Label	My personal attitude concerning the Recommender tool is.... (1- Unfavourable, 7- Favourable).		
	Type	Numeric		
	Format	F1		
	Measurement	Scale		
	Role	Input		
Valid Values	2		2	4.9%
	3		5	12.2%
	4		7	17.1%
	5		14	34.1%
	6		4	9.8%
	7		9	22.0%

TheusageofDailyRecommenderinourdigitalsalesenvironment enhancescu

		Value	Count	Percent
Standard Attributes	Position	15		
	Label	The usage of Daily Recommender in our digital sales environment enhances customer satisfaction.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	3	7.3%
	3	Slightly disagree	6	14.6%
	4	Slightly agree	21	51.2%
	5	Agree	10	24.4%
	6	Strongly agree	1	2.4%

The usage of Daily Recommender in our digital sales environment increases n

		Value	Count	Percent
Standard Attributes	Position	14		
	Label	The usage of Daily Recommender in our digital sales environment increases net new revenue pipeline.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	2	4.9%
	3	Slightly disagree	4	9.8%
	4	Slightly agree	14	34.1%
	5	Agree	19	46.3%
	6	Strongly agree	2	4.9%

The usage of Daily Recommender tool in our digital sales environment enhanc

		Value	Count	Percent
Standard Attributes	Position	13		
	Label	The usage of Daily Recommender tool in our digital sales environment enhances customer/seller engagement		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	3	7.3%
	3	Slightly disagree	1	2.4%
	4	Slightly agree	14	34.1%
	5	Agree	17	41.5%
	6	Strongly agree	6	14.6%

The usage of Daily Recommender in our digital sales environment makes me mor

		Value	Count	Percent
Standard Attributes	Position	16		
	Label	The usage of Daily Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	1	2.4%
	2	Disagree	2	4.9%
	3	Slightly disagree	2	4.9%
	4	Slightly agree	13	31.7%
	5	Agree	19	46.3%
	6	Strongly agree	4	9.8%

In relation to training and support for Daily Recommender I was provided wit

		Value	Count	Percent
Standard Attributes	Position	18		
	Label	In relation to training and support for Daily Recommender, I was provided with detailed training.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	6	14.6%
	3	Slightly disagree	5	12.2%
	4	Slightly agree	12	29.3%
	5	Agree	13	31.7%
	6	Strongly agree	5	12.2%

The usage of Daily Recommender in our digital sales environment increases t

		Value	Count	Percent
Standard Attributes	Position	17		
	Label	The usage of Daily Recommender in our digital sales environment increases the stress in my work.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	3	7.3%
	2	Disagree	16	39.0%
	3	Slightly disagree	4	9.8%
	4	Slightly agree	9	22.0%
	5	Agree	7	17.1%
	6	Strongly agree	2	4.9%

In relation to training and support for Daily Recommender there has been the

		Value	Count	Percent
Standard Attributes	Position	20		
	Label	In relation to training and support for Daily Recommender, there has been the possibility to receive adequate support if required.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	1	2.4%
	3	Slightly disagree	3	7.3%
	4	Slightly agree	8	19.5%
	5	Agree	24	58.5%
	6	Strongly agree	5	12.2%

In relation to training and support for Daily Recommender I was regularly pr

		Value	Count	Percent
Standard Attributes	Position	19		
	Label	In relation to training and support for Daily Recommender, I was regularly provided with advice and tips for it's usage.		
	Type	Numeric		
	Format	F17		
	Measurement	Ordinal		
	Role	Input		
Valid Values	1	Strongly disagree	0	0.0%
	2	Disagree	4	9.8%
	3	Slightly disagree	7	17.1%
	4	Slightly agree	11	26.8%
	5	Agree	14	34.1%
	6	Strongly agree	5	12.2%

Appendix C- Discriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
The usage of Daily Recommender in our digital sales environment increases the stress in my work.	41	1	6	3.17	1.430
How long have you been working in Sales?	41	4	6	5.44	.673
My personal attitude concerning the Recommender tool is.... (1- Unfavourable, 7- Favourable).	41	2	7	4.98	1.458
The usage of Daily Recommender tool in our digital sales environment enhances customer/seller engagement	41	2	6	4.54	1.027
The usage of Daily Recommender in our digital sales environment increases net new revenue pipeline.	41	2	6	4.37	.915
The usage of Daily Recommender in our digital sales environment enhances customer satisfaction.	41	2	6	4.00	.894
The usage of Daily Recommender in our digital sales environment makes me more efficient in generating pipeline revenue.	41	1	6	4.44	1.074
In relation to training and support for Daily Recommender, I was provided with detailed training.	41	2	6	4.15	1.236
In relation to training and support for Daily Recommender, there has been the possibility to receive adequate support if required.	41	2	6	4.71	.873
In relation to training and support for Daily Recommender, I was regularly provided with advice and tips for it's usage.	41	2	6	4.22	1.173
Valid N (listwise)	41				