Context-Aware Recommender Systems for Improved SME Productivity

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by

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Abstract

SMEs in the UK are suffering from a productivity gap compared to larger companies and must find ways to maximise productivity in order to survive. With the widespread availability of digital tools, there is much choice for SME employees to take advantage of these to improve productivity. Tools can be adopted to improve a range of tasks and activities, such as, digital marketing, accounting, communication, etc. As a result, companies can improve productivity by positively impacting the rate of work, employee mental wellbeing, customer relationships, operational costs, and more.

However, with the rapid increase in the number of digital tools on the market today, it is crucial that users are educated adequately on which tools to implement and how to utilise them.

Context aware recommender systems can effectively learn about a user's context and recommend items that would be suited to their needs. However, the context gathering process is key in determining the output. With this in mind, the research contributes an ontology-based context model (SMECAOnto) which gathers user context from SME employees such as, performance, emotions, and demographics. The context model is then used by proposed SME-CARS to determine a digital tool training intervention for users based on their needs with the aim of increasing effective adoption, and consequently, SME productivity.

SMECAOnto is tested against competency questions through querying to test its effectiveness. The evaluation is promising and contributes a practical solution to the relatively understudied field of CARS and SME productivity.

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Chapter 1 Introduction

1.1 Overview

This chapter presents an overview of the research being conducted in this paper by defining the problem, the research aims and objectives, and the research method being used. The research focuses on the relationship between small-medium sized enterprises (SMEs) and productivity, the ability of digital tools to improve productivity, and the capability of recommender systems to address such problems. A key focus of the research is context-ontology modelling and how it can be used to improve SME training recommender systems for improved productivity. The contribution made is an ontology (SMECAOnto) which aims to gather key user context from SME employees including demographics, emotions, and information about their work environment. This information can then be used to equip a recommender system with the knowledge needed to generate high quality training recommendations relevant to employee needs in order to improve productivity.

1.2 Background and Problem Definition

According to a report by BEIS (Business, Energy, and Industrial Strategy) regarding small businesses and productivity, the United Kingdom has suffered from a productivity gap along with other G7 countries (BEIS, 2018). When assessing labour productivity growth, the UK has also performed poorly compared to other OECD (Organisation for Economic Co-operation and Development) countries (ibid). The SME 'digital gap' is the gap between companies who leverage technology and those who do not. The OECD (2019) found that there is a lag in SMEs undertaking digital transformations leading to increased adoption gaps compared to larger firms as technologies become more sophisticated. Not leveraging appropriate technology has proven to hinder productivity (OECD, 2021). Limited access to finances and poor management practices have also been identified as obstacles that hamper SME growth (Roland, 2018).

1.3 Research Aims and Objectives

The research aims to propose a solution for low productivity among SMEs by presenting a recommender system-based solution which directs the user to relevant digital tool training and increases the effective adoption of digital tools. Research will inform the context gathering process which is crucial to building an understanding of the user and generate high quality recommendations that are useful to the user. A deeper look at the relationship between SMEs and digital tools explores how such tools can improve productivity levels at SMEs and whether recommender systems can effectively contribute to their adoption. The following research objectives will be set to successfully achieve this.

Objective 1: Analyse appropriate literature to build a knowledge base of traditional and state-of-the-art recommender systems.

Objective 2: Investigate productivity among SMEs, their relationship with digital tools, and their journey to digital tool adoption.

Objective 3: Identify requirements for a context **model** (SMECAOnto) which can be utilised in a recommender system for the SME environment to support the uptake of digital tools for improved productivity (taking into consideration the findings from Objective 1 and Objective 2).

Objective 4: Develop a model (SMECAOnto) which builds a clear understanding of the SME employee and their needs for increased productivity.

Objective 5: Demonstrate the model through an **instantiation** (SME-CARS) and evaluate the effectiveness of the model using competency questions.

1.4 Research Method

The research paradigm being used to conduct this study is Design Science Research (DSR). DSR will provide a methodological and iterative approach to conducting and presenting the research. The process model being used to carry out DSR is that proposed by Peffers et al (2007). An outline of the approach is highlighted in Figure 1.

Rigorous research requires building an understanding of the problem area and what has been done to address it previously (Hevner et al, 2004). The process of developing the artefact must begin after an end goal has been clearly defined. Chapter 2 follows this approach by building an understanding around the problem of low productivity and establishing digital tools as a solution. Chapter 2 also reviews literature on the diverse types of recommender systems. This informs the end goal which leverages recommender systems to increase SME productivity through appropriate digital tool training.

Peffers et al (2007) looked closely at the work of fellow researchers who focused on design science across disciplines to establish a design science research process model (see Chapter 3, Table 8). The model is made up of six core activities as follows:

1. **Problem identification and motivation:** The first step consists of defining a research problem. This outlines the problem that will be researched and why a solution is needed. Providing an understanding of the chosen problem motivates the researcher and research audience to find a solution and accept the proposed results (Peffers et al, 2007). This paper will identify low productivity levels within SMEs as the problem being solved.
2. **Objectives of a solution:** Once the problem has been identified, the researcher can establish objectives that need to be achieved to produce an effective solution. In order to have clear objectives, the researcher must consider the requirements of the solution (Eekels and Roozenburg, 1991). Objectives for the research have been identified in section 1.3 and requirements of the ontology being developed can be found in section 5.6.2.
3. **Design and development of artefact:** This step is where the researcher will design and develop an artefactual solution. An artefactual solution could be in several formats depending on its purpose (Hevner et al, 2004). For example, constructs, models, methods, or instantiations (March and Smith, 1995). A context-based ontology (SMECAOnto) will be the model developed in this research. SME-CARS is the instantiation which demonstrates how the model can be used in practice to address the problem of low productivity by increasing digital tool uptake.

    a. A **construct** can be described as a set of concepts or vocabulary pertaining to a specific field. Constructs can be used to establish problems and their respective solutions (Hevner et al, 2004).

b. A **model** utilises constructs and applies them to real world scenarios. These are useful when describing relationships between constructs. They are also useful to discover any other problems within their chosen solution space (Hevner et al, 2004). The model proposed in this paper is SMECAOnto, a context-based ontology which collects user context to build an understanding of the SME employee.

c. A **method** provides a set way of approaching a problem to solve it whilst making use of constructs and models.

d. **Instantiations** allow researchers to examine how their solution performs in a real-world setting. This provides researchers the chance to equip themselves with a more in-depth understanding of their proposed solution and how they can innovate to solve the problem more effectively (Newell & Simon, 1976). This paper proposes SMECARS as the instantiation to illustrate how SMECAOnto could be used in practice.

4. **Demonstration:** During this step, SMECAOnto will be implemented through SME-CARS to exemplify a system which learns about the employee through the proposed context-model and recommends digital tool training. A wireframe will be designed which demonstrates how the user can interact with SMECARS and SMECACOnto in the real world. Querying SMECAOnto will demonstrate how effectively user context can be retrieved from the ontology to generate recommendations for SME-CARS.

5. **Evaluation:** Once the artefact has been demonstrated, the researcher should 'observe and measure how well the artefact supports a solution to the problem' (Peffers et al, 2007). This can be done by comparing the objectives of the solution to the results that have been observed from using the artefact in demonstration (Nunamaker et al, 1991). This thesis will use competency questions for the purpose of evaluating the ontology.

6. **Communication:** The last step in the process model consists of the researcher expressing the problem, the developed artefact, its novelty, rigorous design, and how it could solve the problem identified at the beginning. Sharing the research with the relevant audience whether it be fellow researchers or professionals is an example of communication.

Figure 1 outlines the structure of the thesis and maps it to the aims and objectives that have been defined.

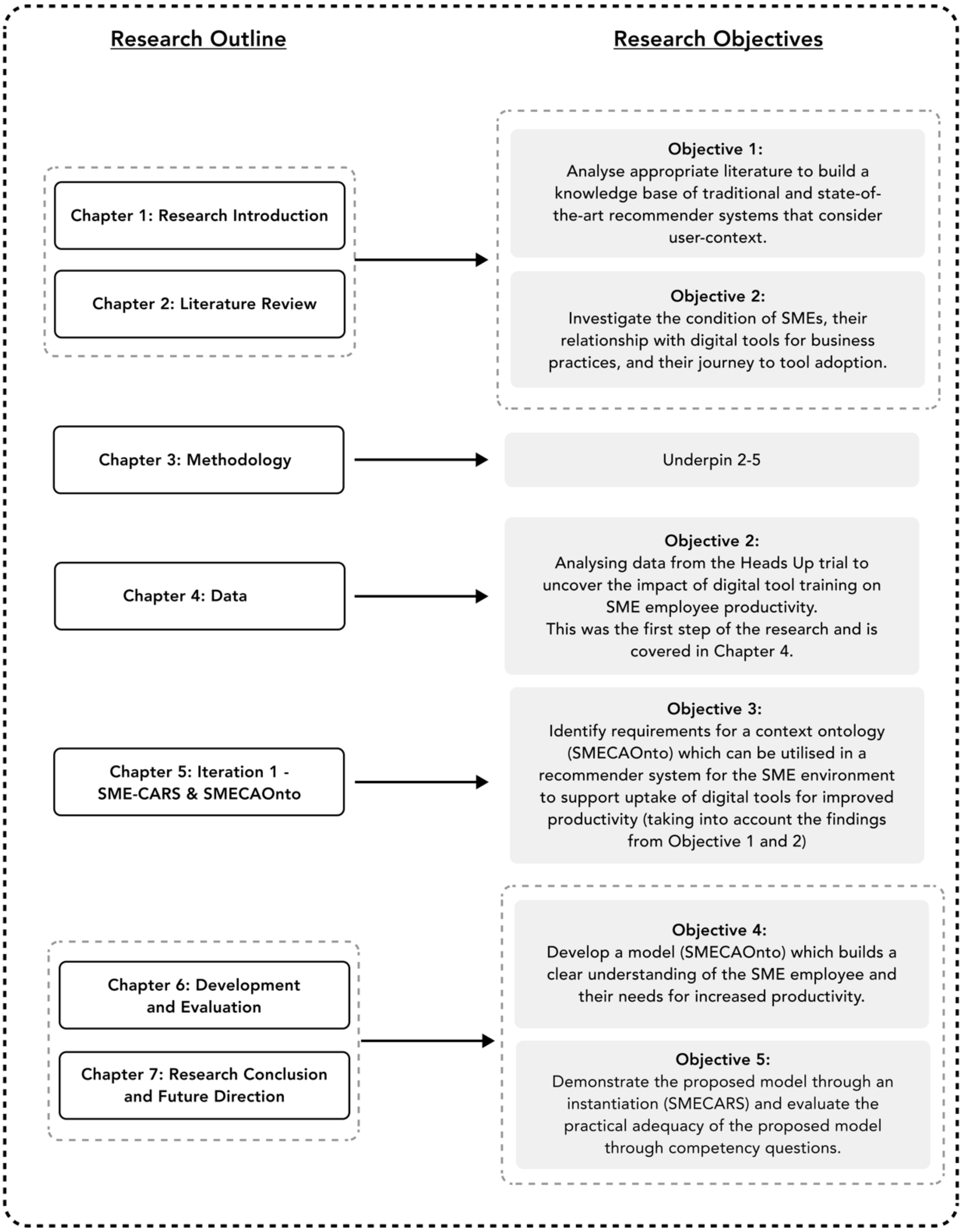


Figure 1: Research outline

1.5 Summary

This chapter has presented an overview of the research and how it will be conducted throughout the paper. Section 1.2 identifies low productivity among SMEs as the problem being addressed and highlights digital tool uptake as one of the solutions. The aims and objectives of the research have been established in section 1.3 and will be revisited at key stages to ensure they are being addressed. The end of the paper will see these research aims and objectives being evaluated to assess how well they have been met. Finally, section 1.4 introduces Design Science Research as the research methodology being followed and outlines the contribution being made in this paper as an ontology-based context model (SMECAOnto). The ontology will be implemented through SME-CARS - a recommender system which uses SMECAOnto to collect context from SME employees and suggest digital tool training so they can more effectively adopt digital tools and increase productivity.

Chapter 2 Literature Review

2.1 Overview

Chapter 2 shapes the research focus of this thesis by reviewing literature on SME productivity, digital tool adoption among SMEs, and recommender systems. The aim of this chapter is to: (1) build an understanding of the relationship between SMEs and productivity; (2) Uncover factors which impact SME productivity; (3) Critically review traditional and state of the art recommender systems to understand the type of system which could play a part in a solution that helps SMEs improve their levels of productivity. Consequently, the findings from this chapter inform requirements for the research contributions proposed in Chapter 5 (SMECAOnto and SME-CARS).

Section 2.2 uncovers the relationship between SMEs and productivity. Section 2.3 focuses on the relationship between digital tools and productivity. Section 2.4 underlines the traditional usage of machine learning that have been recorded in literature. Section 2.5 builds an understanding of how recommender systems are utilised in practice and how they can impact business. Section 2.6 investigates the various types of recommender systems and presents a comparison to highlight the advantages and disadvantages that come with implementing each. Finally, section 2.7 presents a summary of the chapter.

2.2 The SME Productivity Problem

The SME (small and medium-sized enterprise) category is made up of 3 types of enterprises- micro, small and medium (European Commission, 2003). The EU uses staff headcount and financial ceilings to classify companies into the relevant category. To be considered an SME, the company must employ a maximum of 250 employees and have a maximum annual turnover of EUR 50 million.

According to the Department of Business, Energy, and Industrial Strategy (BEIS), productivity can be defined as 'the total output produced per input within an economy (BEIS, 2018). Furthermore, the Organisation for Economic Co-operation and Development (OECD) described productivity as a measure of how 'efficiently' production inputs such as labour and capital are used within the economy to produce a certain level of output (OECD 2018). In the context of this research, productivity is related to each individual employee and how productive they are at work, rather, than how productive the SME is as a whole.

According to Levy and Powell (2004), SME's have a much higher chance of failing compared to larger companies with chances of an SME failing within the first three years being 20% (ibid). SMEs are considered vulnerable since they typically have limited resources and are usually not able to benefit from economies of scale due to their smaller size and reach (Sundar S, 2013). The level of productivity at companies can vary based on the sector they are in, for example, productivity gaps are wider in the manufacturing industry. This requires SMEs to behave differently compared to large enterprises that may operate in the same market (ibid). Smaller enterprises have their own requirements and should not be treated the same as larger companies when trying to effectively influence productivity.

Factors impacting SME productivity can be broken down into internal and external (Marchese et al, 2019). Internal factors are those that business managers can act on order to improve the company's performance. On the other hand, external factors affect the productivity of an enterprise and business owners must shape their decisions whilst considering these external detriments. As outlined in Table 1, workforce and managerial skills are both skill-based factors which could be improved in order to increase productivity.

<table>
<tr><th>Internal Factors</th><th>External Factors</th></tr>
<tr><td>Workforce: The workforce can be adjusted according to what is required from the business at the time. By putting in place the right workforce with the right skills, company productivity can be improved.</td><td>Market: SMEs are the smaller sized firms in a market. It is hard for SMEs to control a market due to their size. For this reason, they must work according to the market.</td></tr>
<tr><td rowspan="2">Managerial skills: Managerial skills such as communication and technical skills can be worked on over time to improve the productivity of the business. However, if these skills are misused SME productivity can suffer.</td><td>Industry: The industry of the firm will influence incentives of business owners as they must keep track of any changes that occur within it.</td></tr>
<tr><td>Local conditions: SME productivity can be affected by their local conditions out of their control. For example, if access to certain resources is restricted, it will affect productivity.</td></tr>
</table>

Table 1: Factors impacting SME productivity (Marchese et al, 2019).

2.3 Digital Tools and Productivity

Adoption of existing modern technologies can enhance operational efficiency and increase productivity (Roland, 2018; Attaran et al, 2019). Digital transformation can help companies adapt to market and technology changes. (Li et Al, 2018). By adopting digital tools and new analytical skills, SMEs give themselves the opportunity to increase the size of the market they serve by not only increasing their reach but improving efficiency (OECD, 2015). Digital tool adoption can also help alleviate the competitive pressure faced by smaller companies (Li et Al, 2016). However, before adopting new tools it is important to acknowledge that they come with learning curves for users. It is not enough for SMEs to simply acquire digital tools to raise their performance as they may lack the resources and capabilities needed to successfully implement the needed tools and benefit from them as intended (Cenamor et al, 2019). A study by the OECD recommends SME engagement with competency centres/technology extension services to receive guidance on effective adoption of digital tools so they may harness digital transformation to boost productivity (Andrews et al, 2019). Table 2 highlights several papers which make a case for digital tool uptake by SMEs in order to improve productivity.

Digital tools help SMEs to	Reference
Reduce operational costs (e.g. automate manual tasks, online banking, digital payments, digital communication)	(Andrews et al, 2019) (Pilat and Criscuolo, 2018) (Garzoni et al, 2010)
Reach larger market and be more competitive. (e.g. social media, digital marketing)	(Andrews et al, 2019) (Pilat and Criscuolo, 2018) (Li et al, 2018)
Operate faster (e.g. documentation tools, digital payment tools, automation)	(Schwertner, 2018) (Lombardi, 2017)
Increase employee productivity (work quicker, reduce stress, organisation)	(Roland, 2018) (Attaran et al, 2019)
Improve relationships with customers (digital communication, social media, customer service software)	(Schwertner, 2018) (Li et al, 2018)

Table 2: Need for digital tools within SMEs.

The research thus far has established low productivity as a problem among SMEs and uncovered the potential digital tools hold to improve it. However, the research has also found a gap in the digital tool adoption process with emphasis being placed on supporting SMEs with appropriate training in order to ensure they are educated on how to use the tools effectively. Machine learning based systems such as recommender systems can collect data from users and personalise the experience to their needs. Tools like this can be leveraged to deliver personalised solutions to SMEs which facilitate the effective adoption of digital tools and improve productivity. The following sections will focus on recommender systems to build an understanding of how these systems could be developed to increase digital tool adoption at SMEs.

2.4 Traditional Uses of Machine Learning

Machine learning algorithms consist of making computers learn from the data they are provided and conduct statistical analysis to provide outputs (Smith, 2018). With machine learning, as the amount of data provided increases, the output produced by the algorithm improves over time (Alpaydin, 2016). Machine learning can be a powerful way to improve the user journey and make a tool more effective over time across a variety of experiences (see table 3).

Machine Learning Example	Description
Spam filters	E-mailboxes consist of spam filters which constantly sort emails that seem as if they are spam into a separate folder. This is the use of a learning algorithm which allows users to only be presented with emails which are relevant.
Facial recognition	Recognition of familiar faces whether it be friends, family, or our own, is also a popular use of machine learning algorithms. These systems become familiar with faces and begins recognising them over time. Facial recognition is a common security measure on phones used to authorise access.
Search engines	Overtime, as users have searched a for items on the internet, machine learning algorithms have used the data to rank pages

	accordingly. Therefore, search results are always changing based on the popularity and relevance of that which the user may be looking for.

Table 3: Examples of technologies using machine learning (Das et al, 2015).

2.4.1 Machine learning approaches based on data type

Supervised learning involves data that is labelled and has structure to it. This type of learning compares an actual outcome against an expected one. With supervised learning, performance of the model can be quantified as discrepancies between the output values and those that have been predicted can be measured (Jiang et al, 2020; Collingwood and Wilkerson, 2012). However, it is crucial that the dataset being used is of good quality and reliable for effective training to be performed on it which often requires a researcher to spend time preparing and pre-processing the data (Muhammad and Yan, 2015). For this reason, it can be understood that the practicality of using supervised learning relies heavily on the access to data and the quality of it. With the increased emergence of AI tools, researchers are emphasising the importance of data-centric AI. Data-centric AI stresses the need to improve the quality of data to unlock its true value which can be done by ensuring the data is consistently labelled (Brown, 2022). Common supervised learning algorithms include decision trees, support vector machines, and Naïve Bayes (Chipman et al, 2012; Christmann and Steinwart, 2008).

Unlabelled data used for unsupervised learning has been gathered by researchers since the 90s using techniques such as web crawlers which can be an easier and cheaper way to collect data compared to gathering labelled data (Blum and Mitchell, 1998). With unsupervised learning, the data utilised by the algorithm is solely the input data with no output data to compare it against. Whilst an unsupervised approach may be useful for discovery purposes due to its ability to find patterns within a dataset, the validity of results is questionable as they are not validated against existing labels in a training set (Baştanlar and Özuysal, 2014; Collingwood and Wilkerson, 2012; James et al, 2013). Clustering is a common machine learning technique that is unsupervised and partitions data into groups. Typical clustering techniques include k-means, hierarchical, and spectral clustering (Allmer, 2014).

2.5 Recommender Systems and their Application

Recommender systems are tools that attempt to predict user behaviour and recommend options to the user based on what the system thinks would suit them. The system uses information about items, the user, and interactions between items and users to make recommendations. (Lu et al, 2015). The goal of a recommender system is described as reducing information overload and providing personalised services by generating meaningful recommendations, for example, items or products (Melville and Sindhwani, 2010).

Recommender systems are a fairly recent area of research with interest around them beginning to rise in the mid-1990's (Admoavicius & Tuhzilin, 2005). This is when internet businesses started to use them to not only improve the user experience, but also create business value. Companies such as Yahoo! and Amazon successfully utilised such systems for the search engine and e-commerce experience (Decoste et al, 2005; Ansari et al, 1999). Research has shown that recommender systems could add business value if implemented correctly (Jannach and Jugovac, 2019). An earlier claim argues the importance of mass customisation rather than mass production if businesses want to maintain customers (Pine, 1993). Schafer et al (1999) assessed recommender systems and found them well-equipped to automate mass customisation. Furthermore, a study of personalised recommendations for Forbes.com users which suggested articles that the user would prefer rather than those that were most recently published, found that users who took such recommendations were more likely to stay on the website for longer (Kirshenbaum et al, 2012). This signifies the importance of recommendations to be personalised for the user in order to effectively convert to business value. Additionally, companies like YouTube found that 60% of clicks on the homepage are that of recommendations (Davidson et al, 2010). A more current example of recommender system utilisation is online entertainment website, Netflix, who believe it is core to their business (Gomez-Uribe and Hunt, 2015). They optimise their algorithms to generate meaningful recommendations of movies/shows to maintain customers by preventing them from spending too much time finding a title to watch which may lead them to lose interest in the platform itself.

Deep learning techniques within recommender systems can allow for accurate results as the model is trained and give way for insightful feature extraction from items like images, videos, and audio (Karatzoglou and Hidasi, 2017). This leads to a more accurate model that allows personalisation so the output provided better suits user activities. Powerful third-party systems have been developed that allow a more straightforward approach to developing recommender systems and make the implementation of recommender systems by smaller businesses more accessible, for example, Google's Tensor Flow (Abadi et al, 2016).

Recommender systems provide an opportunity to automate otherwise mundane processes which require manual effort. The range of recommender systems available today require research into the different techniques employed by each to understand more about how the quality of recommendations generated by the system is impacted.

2.5.1 Recommender systems for SME productivity

The use of recommender systems by technology companies to improve user experience is vast, however, there is less focus on recommender systems tailored to the SME space specifically for the purpose of improving productivity. Some systems have been designed to boost SME productivity as a whole by improving customer retention and creating business value which allows SMEs to compete with larger businesses (Portinale and Brondolin, 2021; Lee et al, 2021; Beel et al, 2019). However, there is a lack of research around using recommender systems to improve SME employee productivity, particularly through digital tool uptake.

Despite the limited literature around recommender systems for SME productivity, Darzi et al (2010) has proposed a hybrid recommender system (FCRS) which combines fuzzy logic and case-based reasoning to generate training course recommendations for SME employees that could help fill skill gaps and as a result increase productivity. Although the work proposes some novel ideas in the space by focusing on SME employee training recommendations, the system determines training recommendations based on information provided by the company rather than understanding the needs of individual SME employees and personalising the training to their needs. There also has not been any significant work related to recommender systems for SME employee productivity since then.

2.6 Types of Recommender Systems

This section presents a more detailed discussion on the different types of recommender systems and their respective filtering techniques. The most common recommender systems are collaborative filtering systems, content-based systems, and hybrid systems (Akhil and Joseph, 2015). Multiple factors contribute to a recommender system's ability to provide useful recommendations, such as, the dataset used by the system, the algorithm used to filter the data, the model used to construct it, and the technique used to build the algorithm. Popular techniques used for recommender systems include bayesian networks, genetic algorithms, probabilistic approaches, and nearest neighbour strategy (ibid). The two core entities required to run a recommender system are the users who use the system, and the items which the users provide their opinions on. Additionally, there are three components which make up a recommender system: input, goal, and output (Vozalis and Margaritis, 2003).

Input:

The input is used to describe the data used by the system to generate recommendations. The type of the input varies depending on the algorithm used to filter the data but typically falls under one of the following types: ratings, demographic data, and content data.

1. **Ratings:** These are also called votes. Ratings are usually made through a numerical scale, such as 1-5, or a binary scale of -1, 0, and 1. (Pranata et al, 2013).
2. **Demographic data:** Personal information such as the age, gender, location of the user. Demographic data is usually collected directly from the user and is therefore harder to collect (Vozalis and Margaritis, 2003).
3. **Content data:** Textual analysis is carried out on data of items relevant to users (Vozalis and Margaritis, 2003). Content data is useful for using features of items and feature values in algorithms as the input (Heinrich et al, 2019).

Goal:

The goal of a recommender system is to provide useful suggestions or predict the suitability of a particular item depending on who the user is. Ultimately, the recommendation should be as accurate as possible when compared to what the user needs. By understanding the goal of the recommender system, we can keep in mind the type of input that must be provided.

Output:

The output of a recommender system can be a prediction which anticipates the reaction of the user to a specific item, or a recommendation of an item which the user is expected to like based on the analysed input (Vozalis and Margaritis, 2003). Table 4 outlines an overview of the structure which makes up a recommender system.

Entities	Input	Goal	Output
User	Ratings	Provide useful recommendations for a user or predict the suitability of that item for the user.	Prediction
Item	Demographic data		Recommendation
	Content data		

Table 4: Recommender system structure (Vozalis and Margaritis, 2003).

Overall, recommender systems must factor in a combination of factors to provide useful recommendations. This includes the type of data available for the input, the algorithm used to filter the data so it is input-ready, and the model and techniques used to generate the recommendations from the data. These systems can automate the process of personalisation for users and cater to their needs. A deeper look at the different types of systems and their functionalities is required to understand which could be leveraged for the purpose of improving productivity among SMEs.

2.6.1 Content-based recommender systems

A common filtering technique used for preparing input data for recommender systems is content-based filtering. Algorithms used for content-based recommender systems extract features from items so similarities can be drawn with the user's preferences. Recommendations are then generated based on similarities between items (Katukuri et al, 2014). For example, regular viewers of action movies receive recommendations of similar movies. Some of the models used to discern the relationship between different items include vector space models and probabilistic models (Isinkaye et al, 2014).

Evaluating recommender systems can be difficult as algorithm performance can vary depending on the input dataset (Herlocker et al, 2004). Additionally, McNee et al (2006) argued the importance of using more than algorithm performance to measure recommendation accuracy. Instead, emphasis has been placed on the importance of considering the user perspective to truly understand the usefulness of recommendations.

Lops et Al (2011) highlighted the increased user independence that content-based recommender systems provide as they do not rely on activity by other users. Instead, they focus on the behaviour of the user and recommend relevant items by finding those with attributes the user has previously liked. Another advantage is the ability of content-based recommender systems to suggest items which may not have previously been rated (ibid). This is due to recommendations being generated based on the item features rather than their popularity.

However, while human preferences are ever evolving, researchers have found that content-based systems suffer from 'overspecialisation' or 'the serendipity problem' (De Gemmis et al, 2015; Kotkov et al, 2016). This refers to the inability of a system to recommend items which are not the user's typical preference thus limiting the likelihood of discovering unexpected items. Schmidt (2021) questions whether artificial intelligence will remove serendipity completely due to its goal of personalising the user experience by predicting user behaviour as well as possible. Iaquinta et al (2008) attempted to introduce serendipity into a content-based system by using an "anomalies and exceptions approach" and found that results with a higher randomness threshold led to better rated recommendations. Additional work by researchers to introduce serendipity has involved the incorporation of natural language processing (NLP), co-clustering, as well as a combination of cosine similarity and an unexpectedness model (Piao and Whittle, 2011; Silva et al, 2018; Jenders et al, 2015).

2.6.2 Collaborative filtering systems

Collaborative filtering (CF) systems consider the opinions of like-minded users by drawing on their similarities to make recommendations rather than basing recommendations on content as seen in content-based systems. (Ryngskai and Chameikho, 2014; Melville and Sindhwani, 2010). For example, a CF system for a movie platform would recommend unwatched movies that users with a similar viewing pattern have watched before. CF algorithms do this by determining patterns from user ratings and interpreting 'votes' or 'ratings' in two ways: explicit and implicit (Jawaheer et al, 2010). Explicit votes rely on users actively interacting with the system, for example, by expressing their like or dislike through methods such as rating. Conversely, implicit votes rely on observing user behaviour to draw patterns, for example, buying an item and returning it indicates that the user did not like the item. This allows developers and designers the flexibility gather information from users in a variety of ways whilst also providing a user-friendly experience.

A well-known advantage of a CF recommender system is the ability to represent individual users and provide personalised results (McFee et al, 2010). However, Gupta and Gadge (2014) identify scalability, sparsity, and cold start, as issues which CF systems encounter. Sparsity is encountered when users do not rate or interact with enough items which leads to limited data available for filtering leading to low quality recommendations. Cold start is another common problem for CF systems which occurs when the system does not have access to data related to new items and new users, for example, when a new user creates an account, data regarding their preferences is not available (Moghaddam and Elahi, 2019). This makes it difficult for the system to generate appropriate recommendations as it cannot find similarities between new and existing users. Much work has been done to address the cold start problem, for example, Zhang et al (2010) introduced social tagging and Lika et al (2014) combined classification methods with demographic data. However, Lika et al's approach helps address cold start best when a large number of users already exist rather than new systems whre there are not many users.

Scalability has also proved to be a challenge for CF systems. Although the recommendations should increase when the number of items and users do, it can be hard for a CF system to draw useful recommendations when the dataset is too large. To generate good quality recommendations, the intricacy of the CF will have to increase as the data set does. This usually requires additional filtering techniques to be incorporated into the system so these issues can be dealt with (Hossein et al, 2013). Lian et al (2018) propose an Implicit feedback-based Content-aware Collaborative Filtering (ICCF) framework which outperformed five competing baselines, including two state-of-the-art location recommendation algorithms. Wang and Blei (2011) incorporate probabilistic topic modelling with traditional CF to generate recommendations of new and old articles as the dataset grows and found that good quality predictions could be made on unrated articles.

2.6.3 Demographic filtering systems

While collaborative filtering draws on similarities between users based on ratings and opinions, demographic filtering systems observe shared attributes between users and suggest items to those with similar attributes. This approach considers all relevant characteristics of the user in order to provide recommendations (Cano and Morisio, 2017). For a human profile, this could include age, gender, location, education history, etc. This information is then used to categorise users and recommendations are based on comparing users who may fall under similar categories.

Unlike content-based and CF recommender systems, a demographic filtering recommender system can generate recommendations without any history of user ratings (Burke, 2002). This is done by using demographic information to shape its recommendations. Wang et al (2018) investigated the usage of demographic information alone to make recommendations to tourists when they are in a new location. Although they were able to predict ratings that users may give, the accuracy could be improved if a hybrid system is utilised rather than a solely demographic one. Whilst sharing the same demographical information with a group does not necessarily mean they will share interests, this information can be combined with other information that the system may collect to learn more about the user and improve the quality of recommendations (Pazzani, 1999, Ghazanfar and Prugel-Bennet, 2010). However, gathering demographic information can be challenging due its sensitivity and the privacy issues surrounding the collection of such data (Mohamed et al, 2019).

2.6.4 Hybrid systems

Hybrid systems have been proposed to address the many issues that are present in all types of recommender systems. Hybrid systems aim to produce a model that is balanced by incorporating techniques from more than one recommender system. Most popularly, these systems adjust content-based and CF systems to develop a framework that enhances the benefits of both systems whilst decreasing the weaknesses (Hossein et al, 2013). Researchers also commonly combine collaborative filtering and demographic based filtering to develop systems that address cold-start, efficiency, and accuracy (Wang et al, 2012, Sridevi and Rao, 2017). A common trend in the research of recommender systems is the need to combine recommendation generating techniques to 'achieve peak performance' (Burke, 2002). Shi et al (2015) found hybrid recommender systems to be the most ideal type of system as one algorithm is unlikely to meet all the needs of a system at the same time. Deploying algorithms that complement each other are more efficient in fulfilling the diverse needs of users which leads to an increase in the user satisfaction rate. However, like most recommender systems, hybrid approaches can also suffer from cold start as well as sparsity. Panigrahi et al (2016) proposed a hybrid algorithm utilising K-means and Dimensionality Reduction techniques such as Alternating Least Square (ALS) to solve the scalability and sparsity problem present in most hybrid systems.

2.6.5 Context-aware recommender systems (CARS)

Context is "any information useful to characterise the situation of an entity that can impact the way users interact with systems" (Abowd et al's, 1995). A system that is able to build awareness about a user's context is better equipped to generate more personalised and accurate recommendations (Haruna et al, 2017). Context-aware recommender systems (CARS) have been designed for this purpose and factor in the context of the user during the recommendation process to generate a more useful set of recommendations. Similar to CF systems, contextual data can be collected explicitly by asking the user or implicitly from the user's environment, for example, time, day, season, or location (Misztal and Indurkhya, 2015). Context-triggered actions can be described as ‘simple IF-THEN’ rules which are used to specify how context-aware systems should adapt to produce recommendations that are useful to the user depending on their specific situation (Schilit et al, 1995). Context-aware systems also hold an advantage when working with a large amount of data. Understanding context of entities in a large dataset allows the system to make comparisons among users who share similar contexts and make recommendations (Subbu and Vasilakos, 2017).

However, research has emphasised the challenges of a context-aware system from a development perspective as there is no unique definition of ‘context’ across disciplines due to its complexity and broadness (Sassi et al, 2017). To address this issue, the pre-filtering process of developing a recommender system consists of either defining or following a model that outlines contexts and their relationships. Data is collected and structured accordingly so that it can be processed by the system to generate valuable recommendations. However, there is still no generalisation of the algorithmic approaches for context-aware recommender systems as they are still a fairly new area (Raza and Ding, 2019). Contextual preferences and their nature can vary greatly, making it difficult to establish a general process for developing the system.

Misztal and Indurkhya (2015) extend CARS by proposing CARE, a context-aware recommender system with explanations. They highlight the importance of providing users with rationale behind the recommendation made to them. Ana and Moriso (2019) provide insight into the algorithmic approaches for CARS and highlight methods for Matrix Manipulation that include Singular Value Decomposition (SVD), Latent Dirichlet Allocation (LDA), Principal Component Analysis (PCA), and similar matrix factorization techniques. Matrix manipulation methods are often used to build low error collaborative recommender systems, however, traditional model-based collaborative approaches like Matrix Factorisation can be inefficient (Karatzoglou et al, 2010). Instead, a Tensor Factorisation method which is a generalisation of Matrix Factorisation has been used for CARS. This allows for a more flexible model which enables easier integration of contextual information into the matrix. Where a traditional 2D matrix consists of User-Item (see figure 2), Karatzoglou et al's, proposal of an N-dimensional tensor, is made up of User-Item-Context (see figure 3). The model is formally known as Multiverse Recommendation Model. It was concluded that the model improved up to 30% upon contextual matrix factorization when considering Mean Absolute Error (MAE). Over the years, Bandit algorithms such as Latent Dirichlet Allocation (LDA) and Markov methods are being used frequently in CARS, however Matrix Factorisation and Tensor Factorisation are still proven to be more popular among developers (Raza and Ding, 2019).

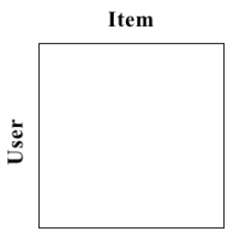


Figure 2: Traditional 2D matrix

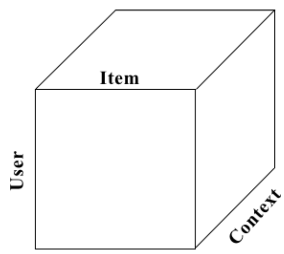


Figure 3: N-dimensional matrix

Context models can help define context data and store it in a way that allows the machine to process it. The large variety of context makes this a difficult process which is why different types of context models have been proposed for building a CARS as seen in table 5 (Strang and Linnhoff-Popien, 2004).

Context model	Description
Key value model	This model consists of a key-value paired data structure to describe capabilities of a service.
Mark-up scheme model	Hierarchical data structure made up of mark-up tags which are associated to attributes and content.
Graphical model	Graphical models such as Unified Modelling Language (UML) can also be used to model context.
Object-oriented model	This model works the same as an object-oriented programming language. It uses objects to represent contexts (e.g.; location) and stores the details of that context within the object.
Logic-based model	Context models defined as results of following a logic-based model are structured to include facts (contextual information), expressions, and rules. The model can then consider new facts and add, update, or remove them.
Ontology-based model	These models represent descriptions of concepts and their relationships. Many context-aware frameworks make use of ontologies as their context models due to their flexibility in expressing relationships.

Table 5: Types of context models for CARS (Strang and Linnhoff-Popien's, 2004).

2.6.6 Ontologies for context-gathering

An ontology is a model that defines the properties present in a specific domain and their relationship with each other in order to build a shared understanding and reduce ambiguities (Guarino et al, 2009; Krummenacher and Strang, 2007). Evaluation of context-aware systems has found ontologies to be the most expressive context model due to their ability to display relationships when defining context and develop a shared understanding around a domain (Strang and Linnhoff-Popien, 2004; Buriano and Marchetti, 2006). Over the years, researchers have introduced ontologies to handle context, however, the broadness of data restricts them to the domain for which the recommender system is being developed. Benlamri and Zhang (2014) introduced an upper-level ontology with sub-ontologies which outlined the multiple interrelated facets involved in the user journey for their respective domain, for example, for e-learning this involved the device, environment, learner, activity, and domain itself. Aguilar et al (2018) presented CAMeOnto with the purpose of proposing a more general ontology which could be used across various domains in order to gather context. The context is categorised as internal (e.g. personal information and emotions), external (e.g. physical context), and boundary context (activities and services). While CAMeOnto may prove too general for many domains, it could provide a scaffolding to follow when creating a domain-specific ontology. Additionally, while context varies extremely across domains, researchers have often categorised context pieces using the '4 (or 5) W's'; who, what when, where, and why (Aguilar et al, 2018; Gasparic et al, 2016). This general approach towards categorising context allows for it to be organised at a high level and provide the context some sort of structure regardless of the domain which it belongs to.

Bobadilla et al (2013) highlighted the progression of recommender systems using content-based or demographic-based data for the first generation of recommender systems to eventually gathering context from social networks using web 2.0. It was also claimed that the third generation of recommender systems will gather context using web 3.0 which consists of information provided by integrated devices on the internet (ibid). This claim can be supported by looking at the recent research and contributions towards the space, many of which leverage the internet of things to gather more context about users for recommendation purposes (Amato et al, 2013; Valtolina et al, 2014; Felfernig et al, 2017; Erdeniz et al, 2018; Patel and Patel, 2020).

Villegas and Müller (2010) emphasised the importance of modelling and managing dynamic context when implementing smart services and interactions which led them to categorise context across five categories: individual, location, time, activity, and relational. This information can help define context types to filter data for a context-aware recommender system.

1. **Individual context:** This is the information collected about individual entities (users/items) that may have similarities. For example, weather, payment preferences, hardware/software used by the user.
2. **Location context:** Locations could be physical places like a specific city, or it could be a virtual location like an IP address. It could also be a place like a cinema or restaurant.
3. **Time context:** This information could represent the time, day, or season.
4. **Activity context:** Considers the tasks performed by the entities. For example, exercising at a certain time of the day, or for a certain length.
5. **Relational context:** This refers to relationships that may be determined because of circumstances that entities are involved in. For example, social relationships with associations, or functional relationships where an entity may make use of another object or organisation.

2.6.7 User interface design of recommender systems.

Recommender systems process data and work in the background to generate recommendations for users. When the data is collected implicitly, for example, user location, time, weather, etc, it is usually gathered from the user's system rather than from the user themselves. However, when the data is collected explicitly from the user, e.g, personal information or preferences, it is collected directly from the user through a user-facing interface (ref). When data is collected directly from the user, the interface plays a crucial role in the generation of recommendations, and the design can impact the quality of data that is collected. For example, if the system required users to rate an item, there could be buttons present on a screen for the user. However, if the positioning or design of these buttons is such that the user cannot give an honest representation of their rating, the data being fed into the system is essentially inaccurate and will lead to low quality recommendations (Cosley et al, 2003).

Whilst user interface plays a role in the quality of input data collected for the recommender system, intentional design of the recommendation output interface is also an important consideration that can increase the likelihood of recommendation uptake by users. User interface can positively impact the user's perception of recommendations if designed in a way that increases trust between the user and the recommender system. One of the design patterns that increase trust is 'Explanationn of Recommendations' which builds user trust in the recommendations generated for them (Cremonesi et al, 2017). Explanation interfaces provide explanations of exactly what the user is being recommended and why, thus leading to increased user acceptance (Pu and Chen, 2007). Furthermore, organization-based interfaces that display recommendations by categorising trade-off properties are considered more trustworthy by users compared to interfaces which simply explain 'why' (ibid).

Although recommender system design has been commonly explored for content-intensive multimedia applications, the idea of increasing transparency around the recommendation process and building user trust by incorporating explanations has been explored briefly with context-aware systems (Hiesel et al, 2016). The same approach can be used for both content and context-based systems to enhance user experience and recommendation impact.

2.6.8 Contributions to the recommender system space

Several researchers proposed recommender systems that address issues like scalability, sparsity, and cold start to improve the quality of recommendations. Table 6 reviews several systems addressing these problems while providing some context about how they work in practice. This builds an understanding of the types of systems which could be used to generate useful recommendations for users whilst effectively addressing some of the well-known issues which have traditionally been present in such systems.

Author	Recommender System Type	Scalable	Addresses Sparsity	Addresses Cold Start	Dynamic	Context/Application
Wang et al (2018)	Content-based				X	A content-based recommender system for academic publications uses a priority order based on the abstract of the manuscript. A web crawler is employed to update the training set and the learning model. A combination of chi-square feature selection and SoftMax regression is used to increase accuracy of recommendations.
Wang et al (2012)	Demographic-based			X		Collects demographic information to make recommendations to tourists about a new area they are in. Whilst their ratings can be predicated, accuracy is limited with demographic information alone.
Sridevi and Rao (2017)	Hybrid (CF and Demographic)	X		X		DECORS: Demographic Collaborative Recommender System. Based on traditional CF, it first partitions the users based on demographic attributes then uses k-means clustering to

						cluster the partitioned users according to the user rating matrix. The system sorts the movie recommendation by increasing order of user preferences.
Wang and Blei (2011)	Collaborative Filtering	X	X		X	Combines traditional CF techniques and probabilistic topic modelling to provide a latent structure for users and items and makes recommendations about both existing and newly published articles. Utilises the CiteULike dataset.
Panigrahi et al (2016)	Hybrid	X	X	X		A User Oriented Collaborative Filtering method which combines both dimension reductionality and clustering methods to overcome common issues found in traditional CF methods like scalability, sparsity, and cold-start. Utilises the MovieLens dataset.
Lian et al (2018)	Collaborative Filtering	X	X	X		ICCF: Implicit-feedback-based Content-aware Collaborative Filtering (ICCF) framework used to make location recommendations scales linearly with data and feature size, and quadratically with the dimension of latent space.
Yu et al (2006)	Context-Aware	X				CoMeR: Context-aware Media Recommendation Platform. Leverages semantic space for infrastructure-based systematic context acquisition to make media recommendations.
Lumbantoruan et al, 2019	Context-Aware			X	X	I-CARS: Interactive Context-Aware Recommender System. Gathers feedback from users iteratively in order learn more about their context and personalise recommendations.

Lumbantoruan et al, 2018	Context-Aware		X		X	D-CARS: Declarative Context-Aware Recommender System. Enables personalisation of contexts exploited for each target user by analysing the viewing history of users.
Misztal and Indurkhya (2015)	Context-Aware		X		X	CARE: Context-Aware Recommender with Explanation. Learns about the user context to recommender items with a rationale which can help the user through the decision-making process.

Table 6: Literature review of studies improving the RS output.

2.9 Summary

This chapter has built the basis of the research in this paper and met research objective two by reviewing literature related to the following areas: (1) The relationship between SMEs and productivity; (2) the contribution digital tools can make towards improving productivity; (3) traditional and state of the art recommender systems. Section 2.2 identified the problem of low productivity among SMEs and possible reasons for it. Section 2.3 suggested online tools as means for improving productivity within SMEs with the caveat that businesses and users must be educated on using such tools for effective adoption. This uncovered a need to bridge digital tool training and digital tool usage for SME employees to effectively adopt these tools. Section 2.6.5 identified context aware recommender systems (CARS) as being able to generate meaningful recommendations given the contextual data being used as input is relevant. The limited research on CARS especially for the SME space has revealed a gap for the development of a domain-specific context model which facilitates a deeper understanding of SME employees.

Chapter 3 Methodology

3.1 Overview

Chapter 3 introduces Design Science Research (DSR) as the selected research methodology and outlines how it will be applied at each stage. DSR will help translate research findings into a solution which improves productivity among SMEs.

Section 3.2 selects DSR as the chosen methodology for the research and outlines the background behind the approach to highlight why it is best suited for the research being conducted. Section 3.3 presents how the methodology will be applied to the at each stage throughout the research iteration, and how this corresponds to the rest of the paper.

3.2 Design Science Research Background

Design science is a research paradigm that aims to create new and innovative artefacts in order to extend the boundaries of human and organisational capabilities (Hevner et al, 2004). The result of design science research concerned with information systems is expected to be a purposeful IT artefact that is created to address an important organizational problem. It must be described in a way that enables its implementation and application to an appropriate domain (ibid). For this thesis, the domain would be SME's. Some may consider Design Science a research methodology, however Iivari emphasises the paradigmatic nature of Design Science as it guides how we approach research as opposed to a set way of conducting the research (Iivari, 2007). Design science takes from a range of scientific theories and engineering methods which lays the foundation for rigorous design science research. March and Smith (1995) compared natural science against design science by stating that "descriptive natural science" tries to understand reality, whereas "prescriptive design science" attempts to create things that "serve human purposes". The intention behind natural science can be considered as descriptive and explanatory. However, design science presents prescriptions leading to the creation of artefacts that represent these prescriptions. They also emphasised that design science is "technology oriented" (March and Smith, 1995).

Peffers et al (2007) created a process model after thoroughly looking at the research conducted on design science by other researchers. They emphasise the nominally sequential order of the steps. It is not necessary for these steps to be carried out in the order of the six steps as they have been outlined. Rather, the researcher can take any approach they feel fits their research best. However, the model as highlighted above gives way for a 'problem centred' approach that begins with identifying the problem (ibid). Table 7 provides further insight into the construction of the process model by breaking down how the different researchers have established the process model and how it has developed over time.

	Objectives for a design science research process model	Archer, 1984	Takeda et al, 1990	Eekels and Roozenburg, 1991	Nunamaker et al, 1991	Walls et al, 1992	Rossi et al, 2003	Hevner et al, 2004
1	Problem identification and motivation	Programming Data collection	Problem enumerations	Analysis	Construct a conceptual framework	Meta-requirements Kernel theories	Identify a need	Important and relevant problems
2	Objectives of a solution			Requirements				Implicit "relevance"
3	Design and development	Analysis Synthesis Development	Suggestion Development	Synthesis, Tentative design proposals	Develop a system architecture Analyse and design the system	Design method Meta design	Build	Iterative search process
4	Demonstration			Simulation, Conditional prediction	Experiment, observe, and evaluate the system			
5	Evaluation		Confirmatory evaluation	Evaluation, Decision, Definite design		Testable design process/product hypotheses	Evaluate	Evaluate
6	Communication	Communication						Communication

Table 7: Design science research process model (Peffers et al, 2007).

3.3 Research Iteration

To conduct this research, the design science research process model developed by Peffers et al (2007) will be utilised. The produced artefacts will provide a solution to the identified problem of low productivity and digital tool uptake at SMEs. Figure 4 outlines the process that this research follows and how it addresses each phase of the selected design science research process model. Peffers et al (2007) clarifies that there can be multiple entry points for the research, including the problem definition, objective setting, design & development, or demonstration. The entry point of this research is a problem centred initiation which began by analysing the results from the Heads Up trial (see chapter 4). The trial showed a clear improvement in productivity as a result of digital tool training however there was a high drop off rate among participants. A literature review solidified the problem of low SME productivity and the need for digital tool training to ensure effective tool adoption before exploring how recommender systems personalise user journeys. The research then focuses on designing an ontology-based context model that learns enough about SME-employees to recommend appropriate digital tool training which can improve productivity. Evaluation is then carried out to assess how effective the context model is in determining SME employee context in relation to productivity.

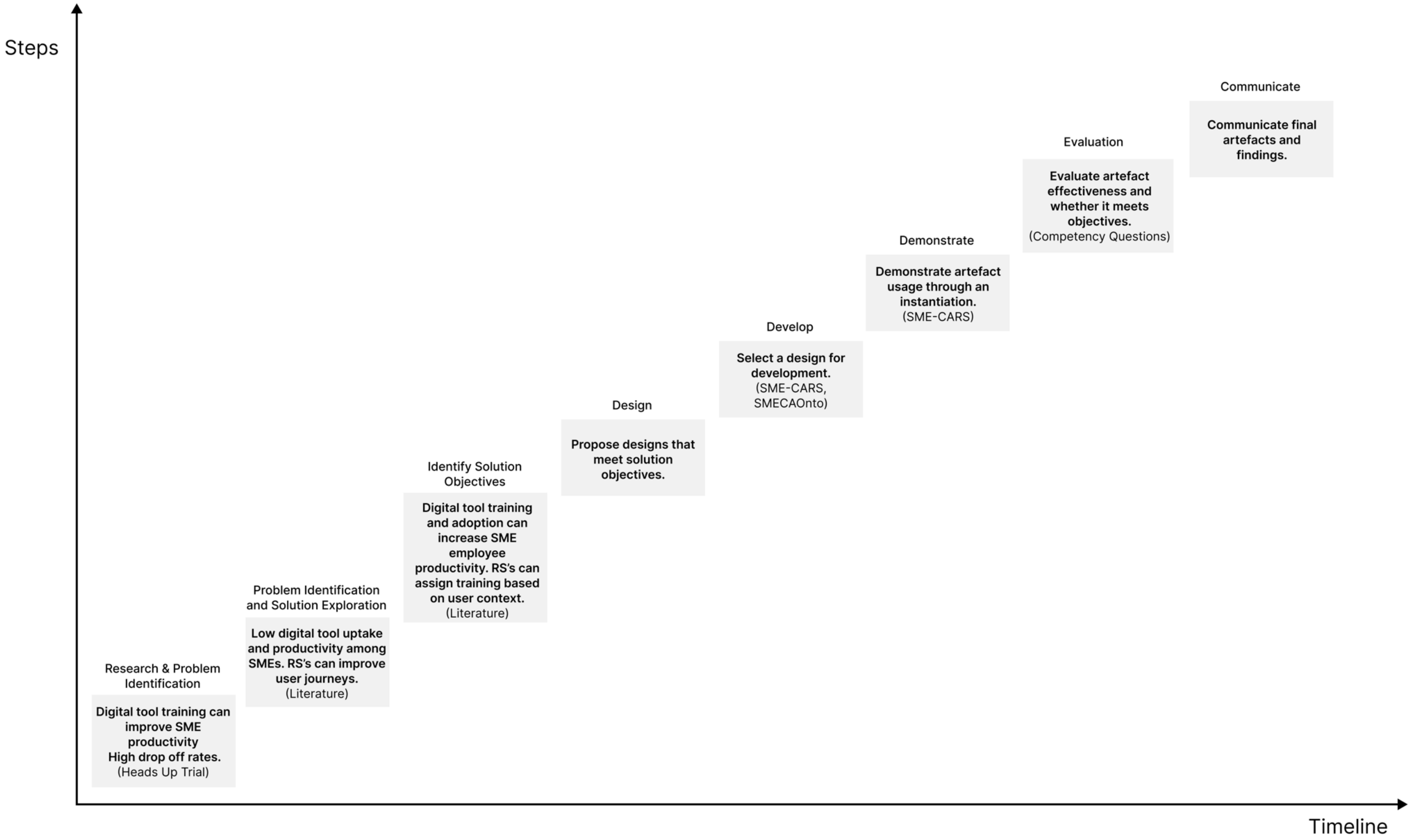


Figure 4: An outline of how DSR will be applied.

3.3.1 Problem identification

The first step of the research was assessing the results from the Heads Up trial which found that digital tool training can increase productivity at work as a result of tool adoption (see chapter 4). A thorough literature review has been conducted on SMEs and their relationship with productivity to highlight the problem of low productivity levels within UK SMEs and the potential causes. The literature also emphasises the need for appropriate training so digital tools can be implemented successfully. This initial stage in the design science research process model provided a firm grounding of the problem that needs to be solved.

3.3.2 Objectives of solution

Objectives are informed by primary and secondary research. The literature review evaluated recommender systems to build an understanding of how such systems could be leveraged to address the defined problem. It also provided insight into the contributions which have already been made and identify gaps that could be addressed in this research by extending earlier work, such as I-CARS. Primary research includes findings from the Heads Up trial analysed in Chapter 4 to better understand the SME journey towards digital tool uptake and how it can be improved. Objectives of a solution will be defined by taking all the research into consideration.

3.3.3 Artefact design and development

Eekels and Roozenburg (1991) include 'tentative design proposals' as a part of their framework. This approach will be followed by generating multiple solutions which could address the identified objectives and one will be selected for further design (see chapter

5). Chapter 5 focuses on the design of the artefact while Chapter 6 details the development. The model being designed will be a domain-specific ontology (SMECAOnto) which gathers user context to build an understanding of the SME employee. The instantiation will be a context-aware recommender system (SME-CARS) which implements the ontology and generates recommendations of training pathways for digital tools which the SME employee can adopt to improve productivity. The ontology-based recommender system will be implemented through a user-facing application. Figure 5 displays how the SME employee will interact with the ontology-based recommender system through the user facing application and what part of the system will define the user context.

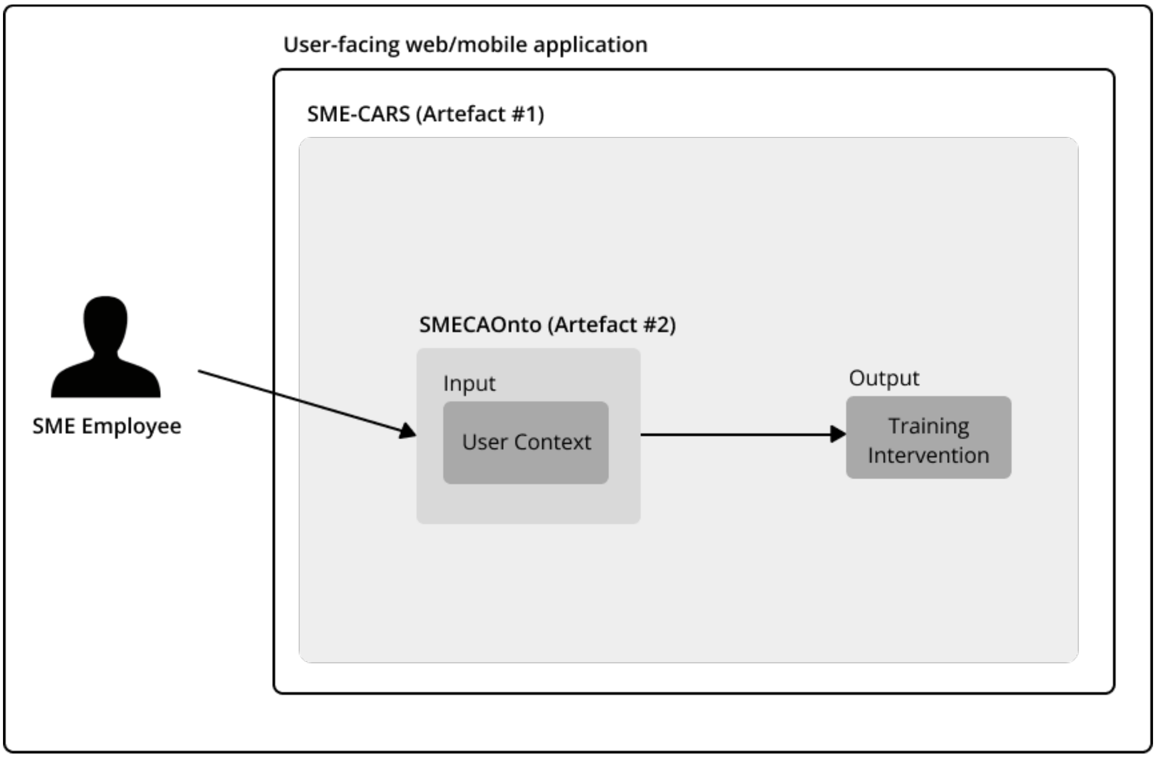


Figure 5: Artefacts being proposed – SME-CARS and SMECAOnto.

3.3.4 Demonstration

Once the ontology has been designed and developed, it will be demonstrated thorugh querying. Querying SMECAOnto will be able to demonstrate how the context would be stored and retrieved if used for a recommender system. This stage provides a breakdown of how the ontology would be used in practice to translate the queried data into intervention levels for each user (see chapter 6). The ontology will be implemented through SME-CARS to show how recommendations of training pathways can be generated for users based on their needs.

3.3.5 Evaluation

Evaluation is a core part of DSR and used to measure how effectively the artefact meets the defined objectives. The artefact will be evaluated by identifying competency questions and using them to test the artefact (see chapter 6). During the evaluation stage, the objectives of the solution will be compared with the results of the artefact to determine how effective it is and to what extent it could be considered a solution.

3.3.6 Communication

The last stage of the research will communicate the final contributions and the findings from the research (see chapter 7). It will also outline any gaps in the research which can be addressed in the future, should the research be extended. Additionally, the chapter shares plans of communicating the artefact and findings to the wider SME and research community with the aim of encouraging further work focused on the intersection of digital tools and SME productivity.

3.4 Summary

Chapter 3 has chosen Design Science Research (DSR) as the methodology that will be used to conduct the research and develop the artefact. The DSR background has been described to provide an understanding of how this research paradigm was developed. This chapter breaks down how the process model developed by Peffers et al (2007) will be applied to the research and how each step will be executed. The upcoming chapters 4, 5, and 6 cover analysis of primary research and detail design, development, and evaluation of the artefact.

Chapter 4 HeadsUp Trial

4.1 Overview

A key part of the DSR methodology is building the knowledge base to help inform objectives for the solution being addressed. This chapter presents an analysis of the data collected through the HeadsUp research study which followed the journey of SMEs going through training of digital tools. Findings will help inform requirements for SMECAOnto and SME-CARS which will be designed and developed in Chapters 5 and 6. Including primary research that is specific to SMEs helps to add rigour to the design process and propose a solution which takes SME behaviour towards digital tool training into account. Including primary research is also helpful due to the lack of research currently available around SMEs and their relationship with digital tool training and adoption.

Section 4.2 outlines the data collection and process provides an overview of the study. Section 4.3 and 4.4 describe the survey design and execution. Section 4.5 details the key findings from the study by conducting tests that prove or disprove statistical significance. Lastly, Section 4.6 highlights how the Heads Up results will inform the next stages of the research.

4.2 Data Collection

The HeadsUp trial was conducted by Brunel University London in partnership with Enterprise Nation. The research was based around the theory that encouraging SME employees to adopt digital tools would lead to an increase in productivity by reducing the time spent on business activities. The study assessed SME employee attitude towards training and the adoption of digital tools after undertaking training.

The same types of training were offered to all participants. Trainings were categorised broadly into four topics:

- **Automate the accounting:** Training was related to banking and accounting.
- **All together:** Training was related to collaboration within an SME and teamwork.
- **Selling in your sleep:** Related to sales and marketing.
- **Stay focused:** Related to staying focused and manging time.

4.3 Survey Design

The baseline survey consisted of 48 questions including 6 general demographical questions. Demographic data was collected to record characteristics of the SMEs which the employees were working at. The characteristics recorded included:

- Region where participant is based.
- Business sector
- Number of employees at the company

The questions were answered in various formats:

- Likert scale (strongly agree, agree, neutral, disagree, strongly disagree)
- Dichotomous scale (yes, no)
- Interval scale (time spent)

The questions were broken down into 8 categories:

- Banking & Accounting (BA)
- Collaboration (C)
- Marketing (M)
- Sales (S)
- Sales & Marketing (SM)
- Time (T)
- Time-management (TM)
- Productivity (P)

The survey also collected data related to productivity and business activities including how they are conducted. For example:

- The use of online tools for business activities such as sales and marketing, banking and accounting, time management, and business strategy and development.
- Processes related to business activities.
- The typical time spent on business activities weekly.
- Company performance.

4.4 Survey Execution

A total of 543 baseline survey responses were collected from participants who intended to be a part of the training program (see table 8).

	Baseline surveys
N	543

Table 8: Number of baseline surveys.

4.4.1 Intervention types: training pathways

Participants are broken down into 2 pathways – online and offline. Some participants undertook training online whilst others carried out training offline (see figure 6). Online sessions were carried out via the Twilio platform, whilst offline training was carried out in person at various locations around England. Online training is known as 'Sessions', and offline training is known as 'Events'. 12.5% of users were assigned the offline pathway while 87.5 were assigned the online pathway.

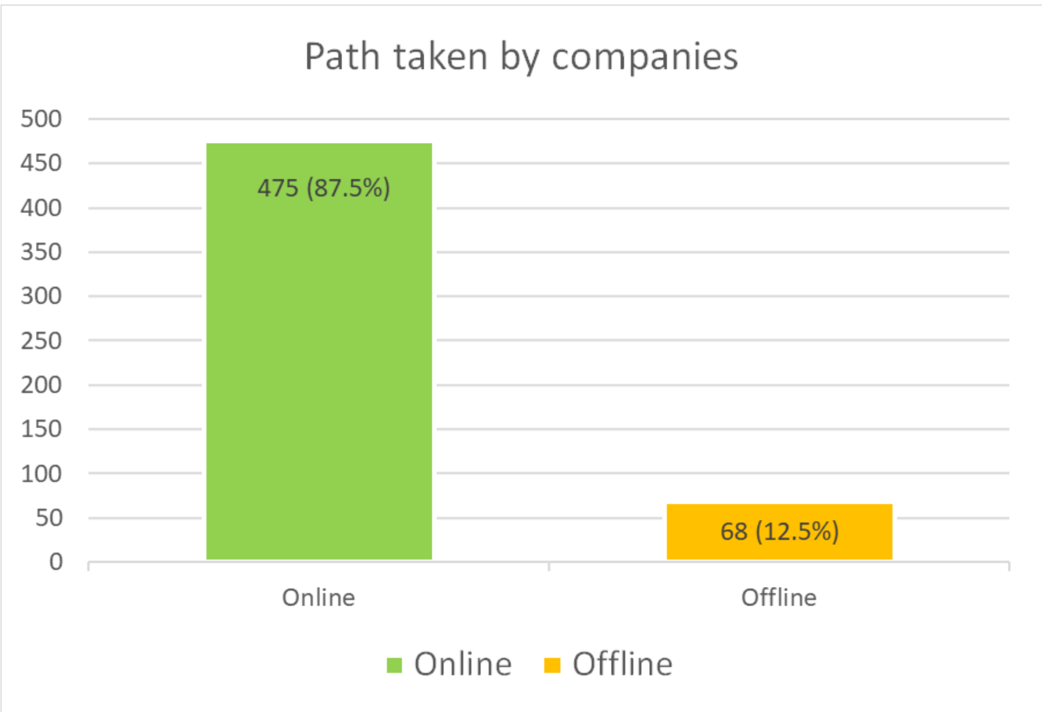


Figure 6: Number of companies taking each path.

4.4.2 Baseline survey vs. post-training survey results

A range of questions were asked in the baseline survey regarding company business activities and the use of online tools for them. The same questions were asked during the post-training survey to determine if there were any changes. There were 48 individual questions related to business activities. A few examples of the most significant changes from the baseline survey to post-training survey are presented in table 9.

Question	Online percentage change	Offline percentage change
Does the company use online tools for Charging Customers/Invoicing?	+5.88%	+14.29%
Does the company use online tools for automating Tax Returns?	+14.71%	-14.28%
Does the company use online tools for Email Marketing?	+7.14%	+9.53%
Does the company use online tools for Customer Retention?	+14.64%	+14.29%
Does the company use online Health and Wellbeing tools to collaborate?	+11.76%	0%
Does the company use online Information Management & Sharing tools?	+2.95%	-14.29%
Do you use apps to help you focus?	+8.83%	+14.28%
Do you use online tools to manage your to-do list?	+2.94%	+28.57%

Table 9: Change in use of online tools for business activities post-training.

The highest percentage increase was 28.57% by offline participants for online tools that manage a to-do list. Conversely, there was a decrease of 14.28% in the use of online tools to automate tax returns. For online participants, there was a significant increase in the use of online tools for customer retention (14.76%).

When asked whether using online tools for business activities had improved productivity, participants answered on the five-point Likert scale. The answers for tools related to the Collaboration training topic were missing from the data. However, the answers for Banking and Accounting, Sales and Marketing and Time Management were collected and showed 60% or more participants felt that productivity improved (see table 10).

	Strongly Agree	Agree	Total Agree
Banking and accounting	27%	38%	65%
Sales and marketing	22%	38%	60%
Collaboration	N/A	NA	NA
Time management	19%	44%	63%

Table 10: Digital tool usage improved productivity.

4.4.3 Post-training survey feedback

41 participants took part in the post-survey training. 34 participants had taken the online pathway and 7 took the offline pathway. The survey provided insight into their experiences of the training as well as the process. The survey addressed the individual outcomes of training for the business and any reasons for not attending, if applicable.

A thematic analysis of the post training survey data presents the training outcomes for SMEs, as well as feedback for the training content and quality (see figure 7). Due to the low number of participants who took part in the post-training survey, the analysis was conducted manually.

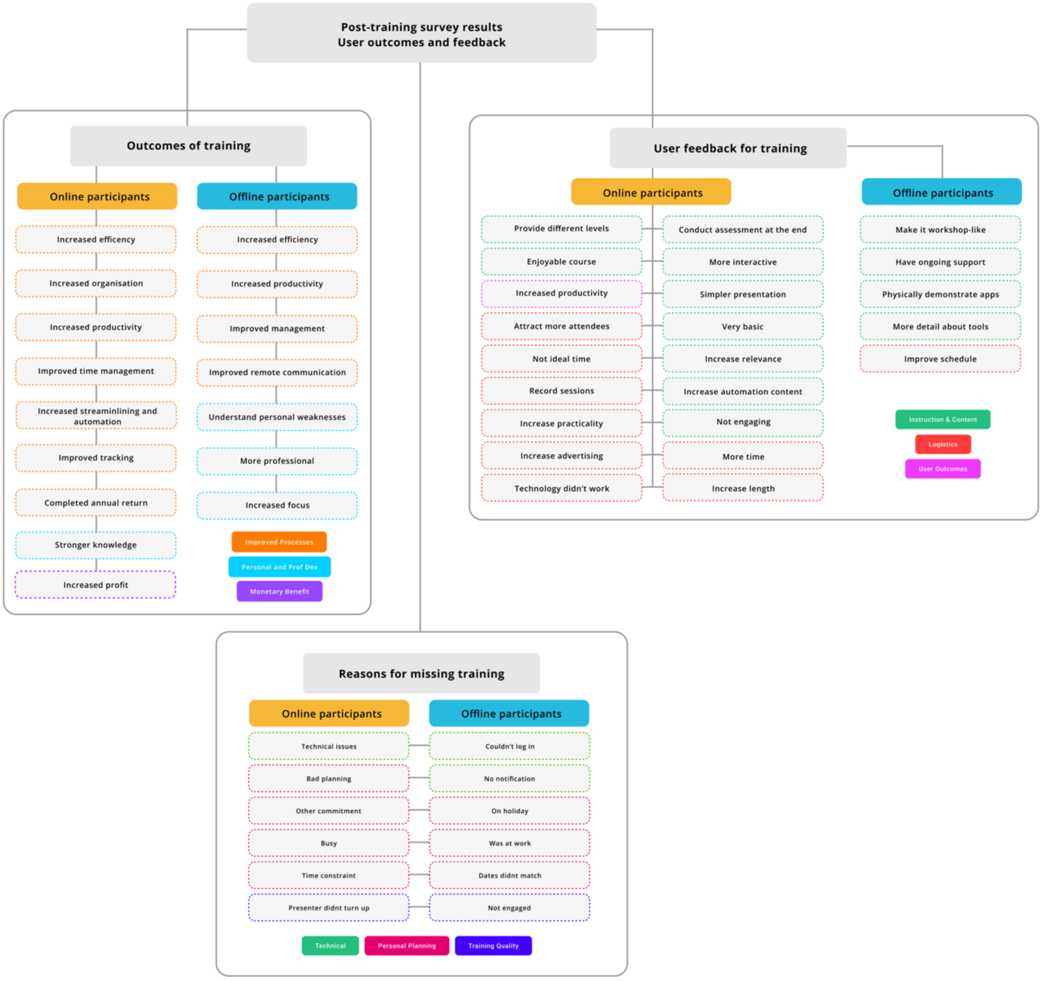


Figure 6: Thematic analysis of feedback.

For offline participants, common feedback included the need for more detail and physical demonstration of online tools that can be used by participants for their business activities. Participants on both pathways found an improvement in self-management to manage their time and resources. Overall, both reported increased efficiency and productivity after training.

The most used tools by participants as a result of the training were mainly cloud storage and analytics platforms:

1. Google drive: A storage platform
2. Google analytics: Analytics platform
3. Outlook: Communication platform
4. Dropbox: Storage platform
5. Zoom: Communication platform
6. Xero: Accounting software

4.5 Key Findings

In order to test for statistical significance in the data, hypothesis tests were carried out. The idea of a statistical hypothesis test is to determine if a data sample is 'typical or atypical' compared to the population. This is done by assuming the hypothesis is true. Conducting the test then leads us to either accept a hypothesis or reject it depending on the results of the statistical test (Emmert-Streib & Dehmer, 2019).

A variation of Chi-Squared Tests and t-Tests were used to analyse the data. The Chi-Squared Test does not assume normality. Although the t-Test does assume normality, it has been considered a robust test with respect to the assumption of normality when comparing two independent samples (Rochon et al, 2012). However, The Chi-Squared Test does not assume the data is normally distributed.

The Shapiro-Wilk Test is recommended to test the normality of the dataset when the sample size is small, particularly where $n < 50$ (Elliot & Woodward, 2007). Godina et al

(2018) also emphasise the increased power of a Shapiro-Wilk Test compared to the Kolmogorov-Smirnov Test. As the sample size of participants who completed both the pre-training and post-training survey fits this criterion ($n < 50$), the Shapiro-Wilk Test is used to test whether the data is normal or non-normal. When testing the offline data for normality before the paired t-Test, it confirmed a normally distributed dataset. However, there was an outlier present among the online participants. In this case, the Wilcoxon Signed Rank Test has been used as a nonparametric approach to support the results from the t-Test (Závadský et al, 2020).

Chi-Squared Test

The Chi-Square Test was used to analyse the relationship between categorical variables (Weerakkody and Ediriweera, 2005). The purpose of this test was to generate a critical value. The critical value combined with degrees of freedom were then used to find the p-value. If the p-value was less than 0.05, the result is considered statistically significant, and we can reject the null hypothesis.

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

Where O_i is equal to observed value and E_i is equal to expected value for the i^{th} category.

Compliance

As used by Hazudin et al (2015), we also carry out a Chi-Square test to analyse the relationship between compliance and pathway. To reach compliance, a total of 2.5 hours of training must be completed by participants. This applies to both online and offline pathways. The length of a single online training session was 30 minutes. In order to reach compliance, online participants had to attend a minimum of 5 training sessions. On the other hand, the length of a single offline training event was 2.5 hours. This meant that in order to reach compliance, participants on the offline pathway had to attend a minimum of 1 training event. We test if there is a statistically significant difference between compliance depending on the participants pathway. In order to do so, the hypothesis being tested is the following:

- Null hypothesis = "There is no difference between online and offline compliance".
- Alternative hypothesis = "There is a difference between online and offline compliance".

The observed values in this case were the total compliant and non-compliant participants for both online and offline pathways. The expected values were calculated using the proportion of online or offline * total compliant or non-compliant participants.

	Compliant	Non-Compliant	
Online • Observed • Expected	18 31.49171270718232	457 443.50828729281768	**475**
Offline • Observed • Expected	18 4.50828729281768	50 63.49171270718232	**68**

	36	**507**	**543**

Table 11: Chi Square calculation for online/offline compliancy.

The further the observed values from the expected values, the more likely that there is a significant difference between online and offline compliance. The formula above and the values in Table 11 are used to calculate the Chi-Squared statistic. It gives a critical value of 49.433422060197477. When looking this up in the Chi-Squared table with 1 degree of freedom, we can see that the critical value is considerably larger than 6.63 which corresponds to a p-value of 0.01. The p-value is significantly smaller than 0.05 which means we can categorically reject the null hypothesis and accept the alternate hypothesis. This proves that the pathway taken by the participant plays a significant part in reaching compliance. The participant is much more likely to be compliant if following the offline pathway as opposed to online. This shows that participants on the offline pathway complete more training before dropping off, whilst online participants are more likely to drop off earlier in the training journey.

Participant drop-off

Table 12 shows a large portion of participants dropped-off at some point in the journey. The number of participants that were remaining by the end of the journey were drastically lower than those at the beginning. This is the case for participants on either pathway. A Chi-Square test is performed to determine if there is any statistical significance related to pathway and drop-off.

The hypothesis being tested is:

- Null hypothesis = "There is no difference between drop off of participants on the online and offline pathway".
- Alternative hypothesis = "There is a difference between drop-off of participants on the online and offline pathway".

	Dropped off	Stayed on	
Online • Observed • Expected	460 456.6298343	15 18.37016575	**475**
Offline • Observed • Expected	62 65.37016575	6 2.629834254	**68**
	522	**21**	**543**

Table 12: Chi-Square calculation for online/offline drop-off.

The result of the p-value was 0.02. This statistically significant result suggests that there is an association between drop-off and a participant's pathway. This leads us to reject the null hypothesis and accept the alternative hypothesis.

Time spent on training

An independent sample T-test was carried out to test if there is a difference in length of training attended by each pathway (Khanh and Thi, 2015). This was done in order to determine if there was a significant difference between the amount of training attended by the two groups. The results confirm significance which underlines that there is a difference between the time spent on training by each pathway.

In order to work out which of the two pathways conduct more training, a one-tail t-Test is used. Before the test, variances between samples must be determined. Carrying out the independent sample t-test also observes the results from the Levene Test (Kusumaningtyas, and Suwarto, 2015). Doing so presents a significance that is < 0.05. This leads us to assume unequal variance. To test the one-tail hypothesis, a t-Test Assuming Unequal Variances is performed. The one-tail hypothesis being tested is:

- Null Hypothesis: Attendees of offline workshops do not complete more training than online attendees.
- Hypothesis: Attendees of offline workshops complete more training than online attendees.

Conducting the t-Test Assuming Unequal Variances returns a p-value=0.0001 which rejects the null hypothesis. Therefore, we can conclude that attendees of offline workshops complete more training than online attendees.

Time spent on business activities (offline)

Restrepo-Morales et al (2019) use the paired t-Test to analyse the effects of various activities on SME's. In the same way, the paired Two Sample t-Test for Means (two-tail) was conducted to determine the difference between the pre- and post-training to analyse if there is a difference between average time spent on business activities before and after undertaking a training program. The test was run on participants who did not drop off during the journey and had conducted both the baseline and post-training survey. Participants had attended at least one training session/event.

The hypothesis being tested was the following:

- Null hypothesis = "There is no difference in the mean time spent on business activities for offline participants before and after undertaking training".
- Alternative hypothesis = "There is a significant difference in the mean time spent on business activities for offline participants before and after undertaking training"

As per the results, the p-value is 0.2 (see Appendix A for two-tailed t-test results - offline). This indicates that there is no significance in the in the change in time spent on business activities for offline participants after they underwent training. Therefore, the null hypothesis is accepted. However, it is worth noting that although there was no statistical significance, there was still a decrease in the average time spent on business activities per week after training for participants on the offline pathway.

Time spent on business activities (online)

Another test was conducted in order to test if there was a change in time spent on business activities by participants that were on the online pathway before and after attending training.

In this case, the hypothesis being tested is the following:

- Null hypothesis = "There is no difference in the mean-time spent on business activities for online participants before and after undertaking training".
- Alternative hypothesis = "There is a difference in the mean-time spent on business activities for online participants before and after undertaking training"

The p-value was 0.04 which highlights that there is a difference between the time spent on business activities before and after training by online participants (see Appendix B for two-tailed t-test results – online). However, it is to be noted that there is one outlier present among the online post-training data which caused an abnormally high skewness and resulted in a non-normal dataset. (Table 18). For this reason, although the t-Test has been conducted, a Wilcoxon Signed Rank Test is also carried out to corroborate the results with those from the t-Test.

Jones et al (2016) use the Wilcoxon Signed Rank Test to evaluate the impact of various training methods on SME's by comparing means. The Wilcoxon Signed Rank Test was also utilised by Restrepo-Morales et al (2019). This test has been performed to compare means of pre- and post-training data (see table 13). The test checks for statistical significance whilst accounting for severe outliers. The results lead to the same conclusion as the paired t-Test allowing us to reject the null hypothesis. This confirms a difference between the time spent on business activities before and after training for online participants. This reveals that digital tool uptake has been able to reduce the time spent on business activities by employees leading them to be more productive. However, it is to be noted that whilst time spent on activities decreased, there is still a high rate of drop-off among online participants.

Wilcoxon-signed rank test - statistically signific

Pre-T	Post-T	Difference	Positive	|Difference|	Rank	Signed Rank
5	7	-2	-1	2	2	-2
29	36	-7	-1	7	9	-9
34	34	0	-1	0	1	-1
7	20	-13	-1	13	12	-12
46	82	-36	-1	36	15	-15
6	16	-10	-1	10	11	-11
16	14	2	1	2	2	2
27	33	-6	-1	6	7	-7
27	21	6	1	6	7	7
28	41	-13	-1	13	12	-12
25	21	4	1	4	4	4
35	40	-5	-1	5	6	-6
7	11.5	-5	-1	4.5	5	-5
14	34	-20	-1	20	14	-14
9	16	-7	-1	7	9	-9

13 *Positive Sum

-103 *Negative Sum

13 **T-Statistic**

25 **Critical Value**

15 n

5% alpha

Table 13: Wilcoxon-Sign Rank Test accounting for outliers.

4.6 Utilising the Heads Up Results

Data has been collected from various points in the study. The first set of data was collected by having participants complete a baseline survey before training. After training was completed, another survey was conducted to gather training feedback from participants. Observational data collected through the trial helped build an understanding of how participants behaved through the digital tool training journey (e.g. drop off rate, training booked, and training attended). The surveys were used as touchpoints through the trial to understand the individual employee experience (e.g. at their workplace, during training, and post-training impact). The baseline survey has played a crucial role in building an understanding around the problem space, validating the problem of low digital tool usage at SMEs, and learning about the different participants who were involved in the training journey. Assessing the impact of the training with regards to the adoption of digital tools and productivity builds an understanding of how SME employees could be supported on their journey towards increased productivity. Additionally, comparing all the data from the Heads Up trial in relation to the online vs offline training provides insight into how participants responded to each pathway and who those participants were. This data will help define the requirements for SMECAOnto and the recommendation output for SME-CARS.

4.7 Summary

This chapter has presented the findings from a study conducted on SMEs which provided them virtual or in-person training on digital tools to boost productivity. Section 4.5 presents the statistically significant findings which relate to participant compliance, training drop-off rates, and the impact on productivity for participants in relation to their training pathway (online vs offline). The most significant finding was the relationship between reaching compliance and training pathway (see table 11). Participants on the offline path were more likely to reach compliance than those taking the online path. This indicates that participants would benefit more from training by following the offline pathway. Another key finding was the decrease in time spent on business activities for participants after going through training, especially for online participants. The increase in productivity for online participants coupled with their high drop off rates demonstrates the need for more flexible training approaches that consider the user's context in order to place them on a pathway they would benefit from most. The findings in this chapter will help inform requirements for the ontology and recommender system (SMECAOnto and SME-CARS) in Chapter 5, especially in relation to the recommendation output.

Chapter 5 SME-CARS Design

5.1 Overview

This chapter presents the design for SME-CARS - a recommender system that will improve productivity among SMEs by suggesting digital tool training to-enable effective adoption of digital tools. The state-of-the-art system being designed is a context-aware recommender system (CARS) that uses SME employee context in relation to their work, such as, their affective states, progress at work, and environment to determine an intervention. This chapter will outline objectives for a recommender system-based solution informed by the research conducted in chapters two and four. Three design alternatives will be suggested that address the identified problem of low productivity before one is selected for further development. There have been variations of CARS, such as a declarative context-aware recommender system (D-CARS) and an interactive context-aware recommender system (I-CARS) (Lumbantoruan et al, 2018; 2019). This chapter presents SME-CARS as the instantiation in this research – a context-aware recommender system for SMEs which implements an ontology-based context model to gather user context and recommend digital tool training. SMECAOnto is the context model being proposed which helps gather user context for SME-CARS. The solution will be designed in this chapter and developed in chapter 6.

Section 5.2 will reiterate the problem of low SME productivity for which a system will be a designed. 5.3 will describe a context-aware recommender system-based solution to the problem. Section 5.4 will propose multiple ideas for a system that addresses the problem whilst fulfilling the solution objectives. 5.5 selects a suggestion and designs an ontology-based context model (SMECAOnto) and preliminary wireframe for the SME-CARS interface. Finally, 5.6 concludes the chapter with a summary.

5.2 Problem Identification

Low levels of productivity within SMEs, particularly in Europe and the UK have been identified (see section 2.2). The adoption of digital tools has been encouraged by researchers to alleviate competitive pressure faced by SMEs (Lit et al, 2018; Cenamor et al, 2019). However, it was found that only 40% of SME's make use of online tools to manage their internal business processes (Clark, 2019). Additionally, it has been emphasised that it is not enough for SMEs to simply acquire digital platforms to improve their performance. They must be equipped with the appropriate resources and capabilities needed to adopt these tools in a way which allows them to be implemented effectively (e.g. via training) (Li et al, 2018).

5.3 Solution Objectives

Low levels of productivity among SMEs within the UK could be improved by effectively increasing the usage of digital tools. Recommender systems have the ability to personalise recommendations for users based on their needs. Such tools could enable effective digital tool adoption and improve productivity within SMEs by understanding SME employee needs and recommending digital tool training which would be best suited to them based on their context.

Generating useful recommendations for users relies heavily on the quality of data collected from users. The Interactive Context Aware Recommender System (I-CARS) has proven effective in gathering relevant context directly from users leading to recommendations that are useful for the user and personalised for them (Lumbantoruan et al, 2019). This paper will adopt the same approach as I-CARS and propose an interactive recommender system that is adapted for the SME environment. The aim of the recommender system will be to collect relevant context from SME employees and recommended digital tool training that will help them adopt digital tools for increased productivity (Cenamor et al, 2019). By collecting appropriate information directly from users like I-CARS does, the system will be able to recommend digital tool training that suits the user's needs, thus, increasing the likelihood of effectively adopting digital tools and increasing productivity. If the system can successfully gauge SME employee needs and capabilities, it can serve as a catalyst for the adoption of digital tools.

Based on the research study in chapter 4, there are two distinct training pathways that can be taken: online training and offline training. The storyboards below (Figure 7 and Figure 8) have been developed to exemplify the core journey training participants took in the Heads Up trial and highlight opportunities where the journey could be improved by introducing recommender systems. While participants were assigned a training pathway manually in the research study, the storyboard pinpoints exactly at which point the user would interact with a recommender system so they can more effectively be directed towards a training pathway that is suitable for them. The intended impact of incorporating a recommender system into the digital tool training and discovery process would be an increase in training, uptake of digital tools, and as a result, employee productivity at SMEs.

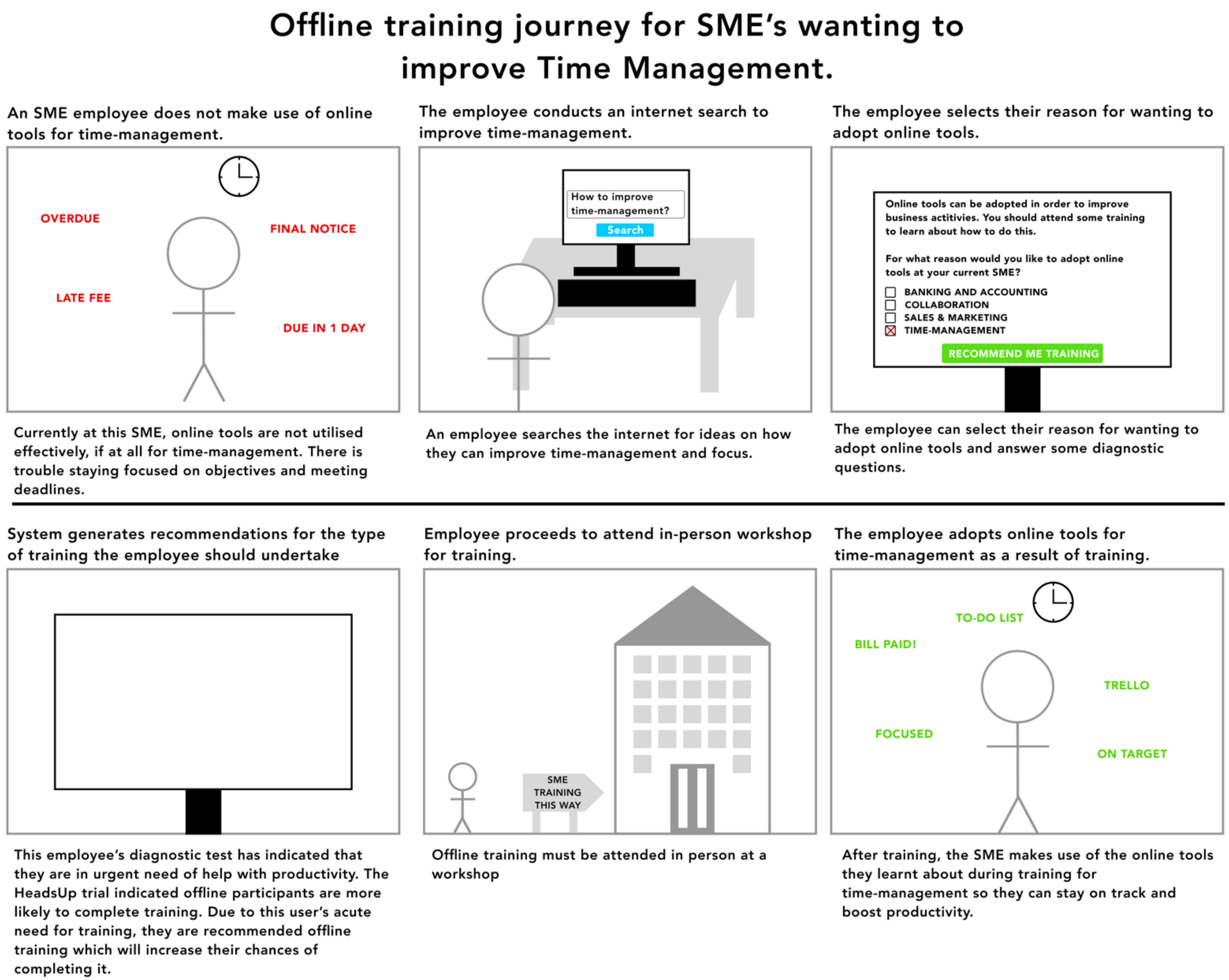


Figure 7: Online pathway user journey

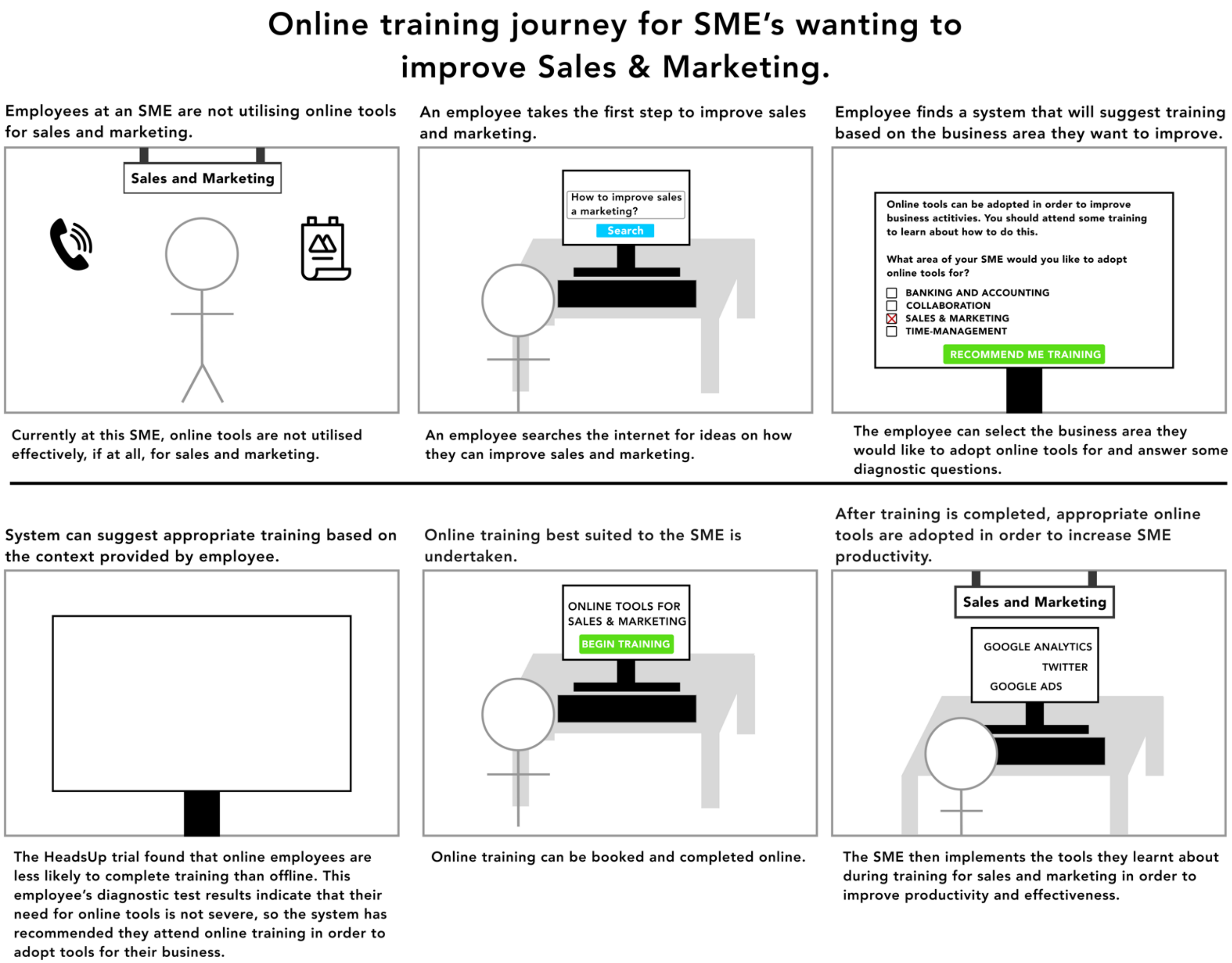


Figure 8: Offline pathway user journey

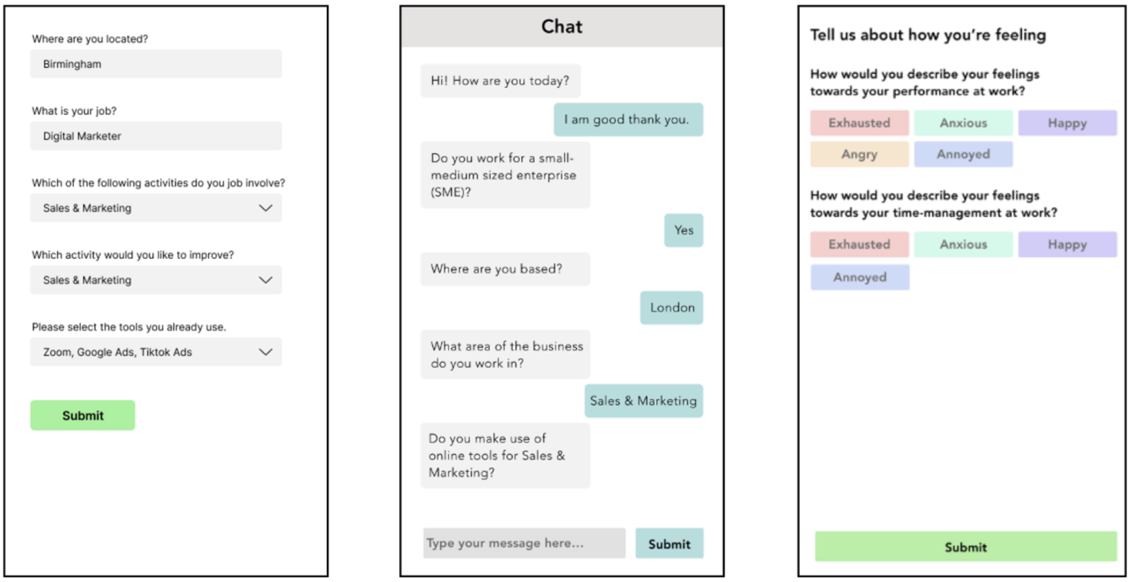
Analysis of individual SME training journeys in the previous chapter has shown that individuals hoping to improve sales and marketing lean towards online training sessions, whilst individuals wanting to focus on time-management are more inclined towards booking offline training. This kind of information can be incorporated into the design of the system in a way that learns about the behaviour of certain groups towards training and improves recommendation quality over time.

Objectives for a solution will the following:

1. Consider the context for each individual user (SME employee) to construct user profiles.
2. Establish the business activities for which the user would like to adopt online tools.
3. Recommend relevant training that would align best with the SME employee.
4. Gather input from the user over time and update profile to follow their journey and measure impact of training and online tool adoption.

5.4 Suggestions

Figure 9 proposes alternative user interface designs for implementation of a recommender system that aligns with the solution described previously in 5.3. The most crucial part of the system will be to gather appropriate context about the user which can then be translated to recommendations. The design suggestions below present alternative ways to do this.



Suggestion 1:
Questionnaire style
context gathering

Suggestion 2:
Chatbot style
context gathering

Suggestion 3:
Context gathering
focusing on emotions

Figure 9: Wireframe design proposals

Suggestion 1: The first suggestion for a solution is a system that recommends online tools or training to users based on a questionnaire about the SME they work in. The context collected is based on the location of the SME, the business sector the company is a part of, and the department the employee works in. Relevant online tools will be recommended based on the employee's business area.

Suggestion 2: The second suggestion is a chatbot style recommender system that allows the SME employee to have a conversation with a bot through which the bot asks questions and collects useful context pieces from the user to generate a recommendation suitable for them.

Suggestion 3: The next design suggestion is a recommender system that continuously obtains contextual information through user feedback. The collected information is utilised by the system to construct profiles for each user. The focal point of the suggestion is the active approach to engage the user and request feedback at specific points in time as opposed to waiting for the individual to use the system when they need help. With this approach, the system follows the journey of the SME and makes training recommendations along the way. A key context piece collected by this system is user emotions. This piece of information will help the system better understand user emotions towards work to determine whether they are stressed, anxious, relaxed, etc, and recommend an intervention based on the user's need. This piece of information will continuously be updated as the user adopts online tools to assess if employee stress levels decrease after adopting online tools.

5.5 SME-CARS

This research will select design suggestion 3 to extend I-CARS by Lumbantoruan et al. (2019). The proposed system will be called SME-CARS - a small-medium sized enterprise context aware recommender system and will keep track of business activities within the SME over time. The system attempts to understand SME employee behaviour towards business activities to create user profiles. This will help to understand user context and continuously gather information on employee attitudes towards work. These attitudes can be assessed over time by the system to determine whether interventions have been effective in improving productivity which can lead to higher quality recommendations. Currently, I-CARS presents an interactive method of gathering contextual information from users in the form of feedback. SME-CARS will also enable the user to interact with the system and provide context. However, it will extend I-CARS by including emotion in the context model. Emotions will be a recurrent context piece which will be collected from users. By comparing the user's emotional well-being to their way of working, the system can propose ways to achieve more productivity in a way that reduces stress or anxiety. By staying involved in the SME journey towards adoption of online tools, the system can update user profiles along the way and assess the impact of said tools on their emotions, performance, and productivity.

To meet objectives one and two, SME-CARS will collect the context of the SME and the area of their business which they would like to improve through some diagnostic questions. The system will then recommend training that will suit their needs and help achieve their desired goals towards increased productivity. Diagnosis questions that can help identify user context will be established by assessing the findings from the questionnaires in chapter 4.

5.5.1 Ontology-based context model

An ontology-based approach will be adopted to design the context model. In the context of this research, the ontology will build a shared understanding of individual SME employee context in relation to productivity in the workplace. The relevant information can then be used to determine SME employee need for training and generate appropriate digital tool training recommendations. SMECAOnto will be designed using the ontology-based approach for CAMeOnto (Context Aware Meta Ontology) by Aguilar et al (2018). The context model for CAMeOnto splits into three context sections: internal, external, and boundary. However, SMECAOnto will consider the context of the employee at the SME professionally and personally to facilitate the collection of richer user context. While CAMeOnto aims to propose a general ontology for any domain, SMECAOnto will present a more specific ontology which can accurately represent SME employee context and their relationship with productivity.

The collected data will help build user profiles which represent each individual user. Professional context includes the user's line of work, work setting, and performance. Personal context includes demographical information and the user's emotional well-being. Emotions will be incorporated into the model as a context piece due their impact on job performance and the impact job performance can have on emotions (M Pervez, 2010; Gong et al, 2019). Furthermore, emotions are dynamic, and change based on individual circumstances, which is why including it as a context piece will provide more insight into the user's well-being throughout their training journey (Mesquita and Boiger, 2014). The impact of suggested training and adoption of online tools will be measured by observing the user's emotional well-being over time.

5.5.2 SMECAOnto requirements

The requirements for SMECAOnto will guide the design of the ontology. By grounding the requirements in research, it will ensure that the design follows a research-based rationale and the context pieces being gathered by SMECAOnto are relevant to the SME employee in relation to productivity.

Requirement 1: Understand the user's emotions towards their work.

The decision to understand user emotions is grounded in research that focuses on the role of emotions on employee productivity. Whiting (1987) suggests that productivity is tied to creative and innovative thinking, however, emotions play an important role in enabling such behaviours (Higgins et al, 1992). Psychological research has also demonstrated the impact of affective states on information processing, memory, and creativity (ibid). Understanding employee emotions can indicate their level of productivity and determine how acute their need for training may be. Tracking emotions over time will also help determine the effectiveness of the recommended training by assessing how the employee feels towards their work over time.

Requirement 2: Understand the user's demographical information.

Demographical information has been identified as a useful context piece when generating recommendations. When suggesting training to users, such data can consider how other users sharing similar attributes have responded to training in the past. This would help improve the effectiveness of recommendations as the system will be more informed to generate targeted recommendations. Analysis of the findings from the Heads Up trial in Chapter 4 found that location played a part in a user's willingness to book training for the pathway they were on. This indicates that demographical data will help the system understand more about the user's likelihood of booking and completing training and identify a suitable training pathway for them. For example, if offline training locations are far from the employee, online training would be the most appropriate pathway for them.

Requirement 3: Gather context about the user's work environment.

An employee's work environment can play a major role in their level of productivity, for example, working fully remote, from the office, or hybrid. (Lund et al, 2020). This has become increasingly apparent during the Covid-19 pandemic. The relationship between the work environment and productivity can vary based on the industry which an employee works in. For example, a florist would be more productive working remotely compared to a chemical technician (ibid). Collecting such data can provide context to user's level of productivity. Additionally, trends can be drawn among user work environments and productivity to establish whether a certain type of training is more suited to them. For example, are fully remote employees more likely to complete online training or offline training which requires them to attend in-person?

Requirement 4: Determine the user's performance at work.

Employee performance at work will be collected in order to track the impact of training on productivity. This will help fine tune recommendations over time as it will help determine whether training is positively impacting employee performance.

5.5.3 SMECAOnto design

Figure 10 presents the design of SMECAOnto and all the different context pieces which will make up the SME employee user profile. Using this ontology to collect data from an employee at an SME can help a system gather the necessary information needed to determine their productivity levels at work and their need for training. The data will then be processed by a recommender system to generate recommendations for digital tool training courses. By designing an ontology grounded in the requirements defined in section 5.5.2, the ontology enables the collection of data that considers the key context pieces related to an SME employee, particularly in relation to productivity.

SMECAOnto is divided into 3 core categories: professional context, personal context, and time. These categories are defined as classes which represent a set of entities or things within the SME domain. Whilst the 'time' class collects the time at which the user submitted the context, 'professional context' and 'personal context' allows collection of a range of information from the user and have their own subclasses with properties associated to them. The subclasses related to professional context collect context about the user's performance, work setup, and environment. The subclasses related to personal context gather context related to demographics and emotional wellbeing. The lower level of the ontology (domain specific ontology) represents the ability to expand the ontology and tailor it by adding subclasses that are even more specific to the domain. The type of arrows used in the ontology have their own purpose. For example, the black filled arrow represents the progression from high level context pieces (e.g. professional context) to more detailed context pieces (e.g. performance). The unfilled arrow on the other hand represents the movement of data. The movement of data represented in the ontology is notational and symbolises the saving of data entered by the user. For example, the user's selected response to their age is saved to the demographical context in the system which is a part of the user profile. Lastly, the legend in Figure 10 clarifies the difference between a class and a property.

As outlined in section 5.5.2, the design of SMECAOnto has been driven by a combination of primary and secondary research. The design of the ontology could be enhanced further by working closely with SME employees and researchers to understand the relevance of the context pieces defined in the ontology and whether there is anything significant which impacts productivity but has not been covered.

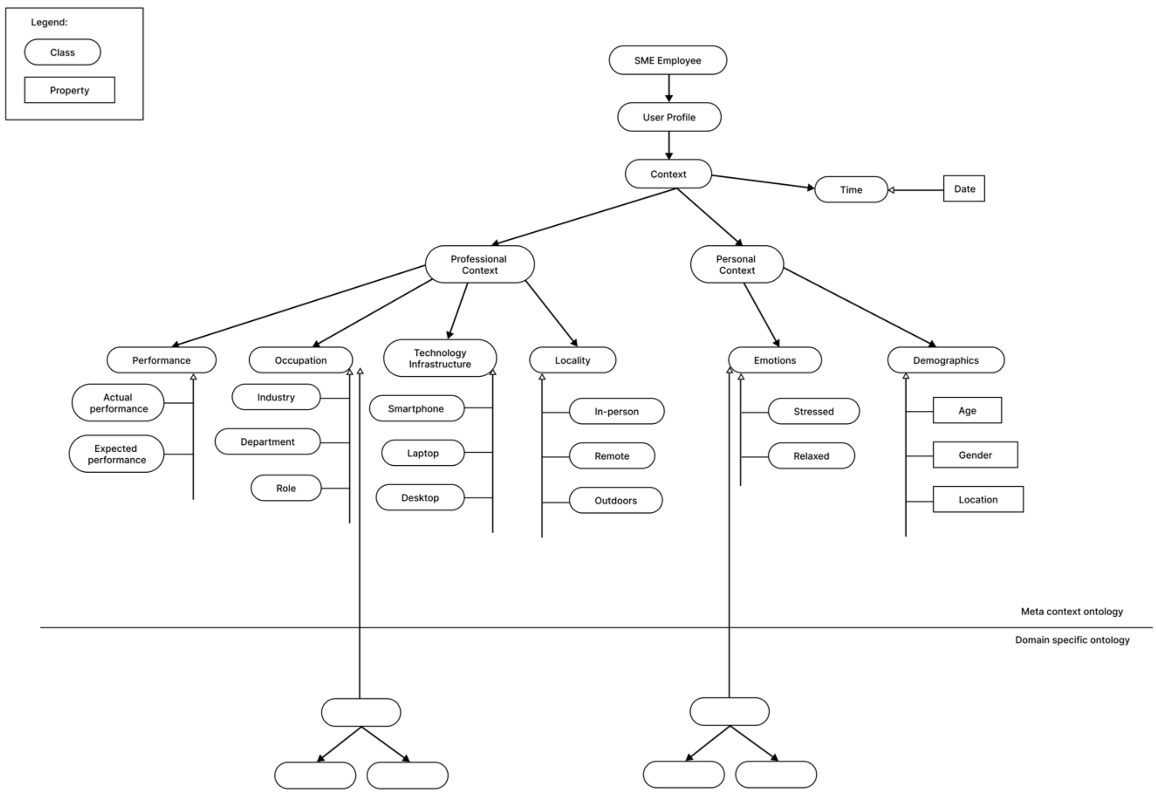


Figure 10: SMECAOnto - SME Context-Aware Ontology

As applied by Aguilar et al (2018) for CAMeOnto, the '4 W's'; who, what when, and where, are used to organise the context being gathered for SMECAOnto (see table 14). This highlights the range of context being gathered to build a well-rounded user profile which will be used by SME-CARS to generate training recommendations.

Context Piece	Who	What	When	Where
Demographics	X			
Emotions		X		
Locality				X
Occupation		X		
Technology Infrastructure		X		
Time			X	
Performance		X		

Table 14: Context pieces categorised using the 4 W's (Gasparic et al, 2016)

5.5.4 Rule base

Incorporating a rule-base into the system will allow information to be extracted so recommendations can be made. There will be an inference module embedded within the system to infer new information by passing already collected data through a set of rules (Mihai, 2017). The inferred information can then contribute to formulating recommendations. Figure 11 illustrates the architecture of a rule-based recommender system to provide an overview of the data flow as it is collected from the user and converted to a recommendation.

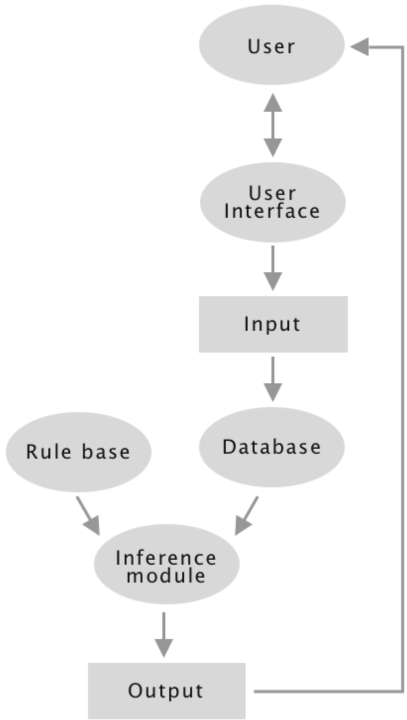


Figure 11: Rule-based recommender system design

5.5.5 Wireframes

The designed wireframes visualise how data will be collected so it fulfils the requirements of the context model (see figure 12). The first screen collects personal information regarding the demographics of the user, such as, gender, age, location. The second screen also collects personal information, but in relation to user emotions. It asks the user about their emotions towards their performance at work and towards their time-management. This information will be used to model the personal context of the user. The third screen collects professional context from the user which includes, the user's industry, role, technology infrastructure at work, and current online tool usage.

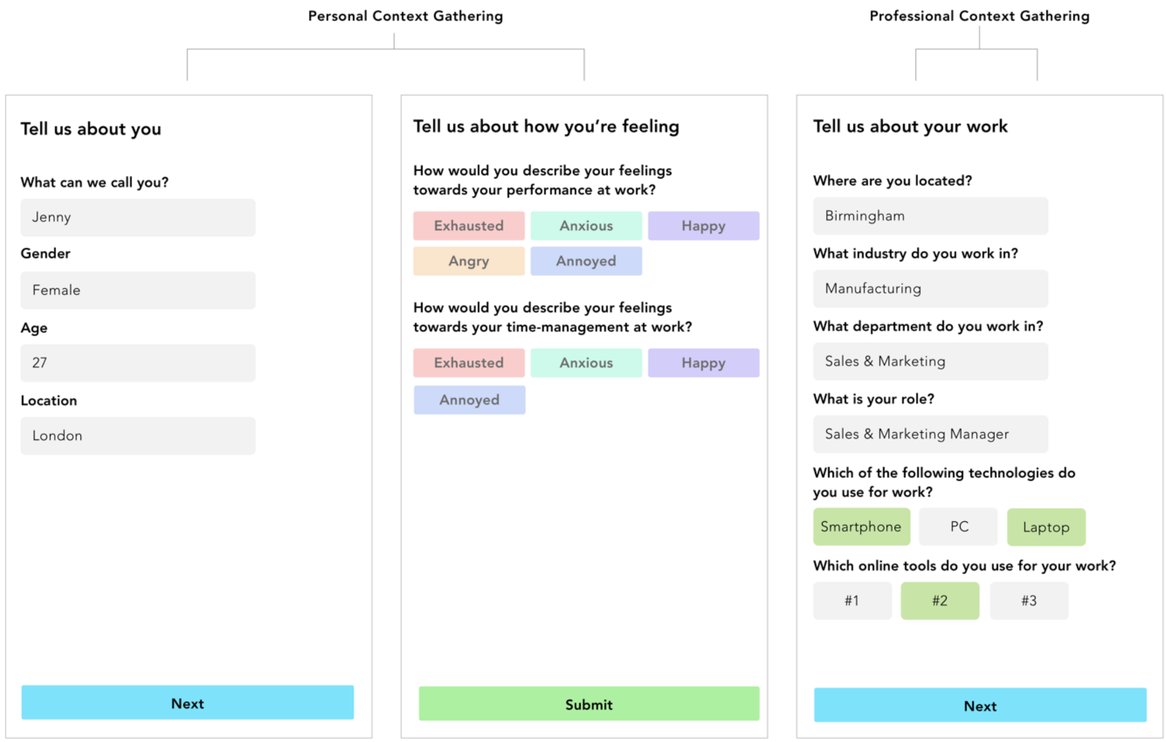


Figure 12: User interface for context gathering.

5.6 Summary

Chapter 5 used the findings thus far to generate design proposals of a solution for the identified problem - a key step in the DSR methodology (section 3.3.3). This chapter proposed context-aware recommender system-based designs that address the problem of low productivity within SMEs by suggesting digital tool training. Section 5.3 used storyboards to illustrate how SME employees may interact with a context-aware recommender system in practice for the purpose of adopting digital tools and improving productivity. SME-CARS – a small-medium sized enterprise context-aware recommender system which extends I-CARS by Lumbantoruan et al (2019) has been proposed in section 5.5 as the instantiation in this research. Section 5.5.2 identified requirements for SMECAOnto which is the ontology-based context model contributed in this research to help collect and categorise context for the recommender system (SME-CARS). The ontology enables collection of professional context about the user's work life and personal context which collects demographical and emotional information. By collecting user emotions, the system will compare them to professional context and infer the level of intervention needed to improve SME employee performance. 5.5.3 presented a visual overview of what the rule base for the system will look like to show how it will process the context (see figure 14). Finally, 5.5.4 presented wireframes which demonstrate how the user will interact with the system to provide context and generate recommendations. Chapter 6 will focus on the SME-CARS instantiation which implements SMECAOnto and describes development and evaluation.

Chapter 6 SME-CARS Instantiation - Development and Evaluation

6.1 Overview

The contribution made in this research has been SMECAOnto which was proposed in Chapter 5. This chapter will implement the context model through SME-CARS: a context-aware recommender system which collects context from SME employees and generates recommendations for digital tool training. Chapter 3 defined design/development and demonstration from DSR as key steps in the research process (see 3.3.3 and 3.3.4). A user-interface will be designed to demonstrate how SME-CARS implements SMECAOnto and enables the user to interact with the system in practice to provide context and receive recommendations. Several user profiles will be developed to capture the properties from the ontology designed in Chapter 5.5.2 (see figure 13). The model will be developed using a NOSQL database and queried at different points in the user journey to demonstrate how relevant context can be extracted for good quality recommendations of digital tool training pathways. The purpose of this process is to test how the data will be collected, stored, and retrieved through the ontology.

Section 6.2 will design a user-interface that demonstrates how context will be collected for SMECAOnto Section 6.3 will develop ten user profiles that are in line with the context model. Section 6.4 will develop the list of interventions to be utilised by the context model. Section 6.5 will query the model to demonstrate how the data stored in the context model could be called at different points in the user journey towards digital tool adoption for improved productivity. Section 6.6 will use competency questions to evaluate SMECAOnto and section 6.7 concludes the chapter with a summary. Table 15 outlines how the research will be conducted in this chapter to cover the demonstration and evaluation steps in the DSR process model along with the expected output.

Section	Step	Input	Output
6.2	Demonstrate how the user will interact with SME-CARS.	Context data and intervention recommendation.	A user-interface that presents how users will interact with SME-CARS so context can be collected, and recommendations can be presented.
6.2	Demonstrate how the ontology would collect and store context.	User context data as it would be collected from a user.	10 user profile that illustrates how the ontology would store data for each user. User profiles will be stored in a NOSQL database for ten user profiles.
6.3	Identify the types of interventions that can be recommended to users.	Data on intervention types from the Heads Up trial results (chapter 4).	A model displaying the possible training interventions that can be recommended to users based on the input data from the ontology. Interventions have been modelled in a NOSQL database.
6.4	Demonstrate how user context will be retrieved from the ontology to identify appropriate interventions for recommendations.	Context data from user profile.	User profile is queried using DynamoDB to demonstrate how SMECAOnto can generate a recommendation of an intervention for the user.
6.6	Evaluate SMECAOnto	Context collected by SMECAOnto	Competency questions to evaluate whether the required data is effectively collected from the ontology.

Table 15: Table of steps for chapter 6.

6.2 SME-CARS User Interface

SME-CARS and SMECAOnto will be implemented through a user-facing survey which collects context directly from SME employees and generates recommendations of digital tool training pathways. The goal of the training is to increase adoption of online tools and improve productivity among SMEs. The wireframe demonstrates how the recommender system would work in practice based on the user's interaction with it. Users will be able to update their data during their journey towards increased productivity at work so that the system can update recommendations along the way. This interactive approach of gathering context from SME employees leads to high quality recommendations as seen with I-CARS. It also allows the system to observe the impact of interventions on the professional and personal context of SME employees over time. This solution focuses on increasing the accessibility to appropriate digital tool training and enabling effective digital tool adoption. Chapter 2 found that adoption of digital tools is not enough for SMEs, they must also be trained on how to successfully use these tools. By understanding the user's context, SME-CARS will be able to match SME employees to a training pathway that is appropriate for them and increase access to relevant digital tool training. The recommendation output interface is discussed further in section 6.2.3. This system aims to increase digital tool adoption at SMEs and ensure they can use the tools successfully for improved productivity by guiding them through the appropriate training pathway.

6.2.1 User profiles

Figure 13 highlights the different screens used to gather the context for the ontology from the employee and how this data then displays a recommendation to users. The user profile is built using the data inputted by the user which the system then uses to calculate an intervention severity (low, medium, high). User's may update the profile information held about them in order to receive an updated intervention level.

6.2.2 SME employee emotion gathering

Emotions have been taken from the Geneva Emotion Wheel (Scherer, 2016) to offer the user a range of affective states they can choose from. By using this model, users can select the emotions that they relate to and feel best describe how they feel. There are over 30 affective states and multiple words that describe each. From this large selection of affective states, a few have been selected to represent positive, negative, and neutral emotions. Applying user selected emotions to the Geneva Emotion Wheel helps deduce whether the selected emotion is closer to negative, positive, or neutral. The response is then applied to a scale so it can be used by the system. Figure 14 displays how the user would interact with the system to select the emotions they relate to.

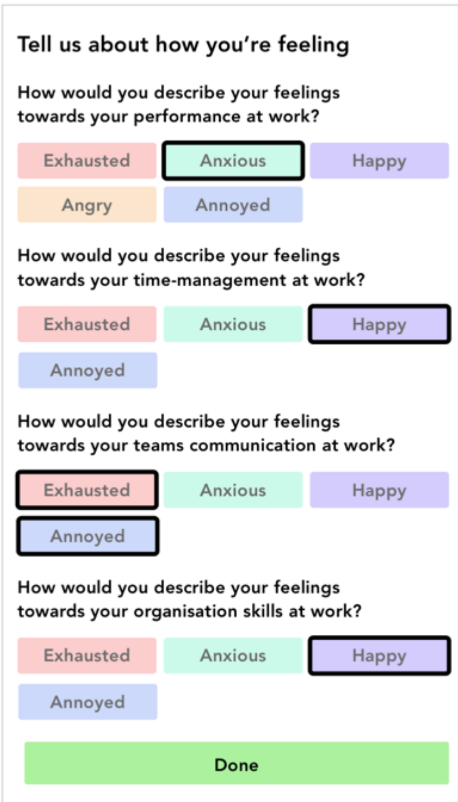


Figure 13: Emotion selection UI

6.2.3 Recommendation interface

The results page has incorporated the ‘explanation of recommendations’ design pattern explained in section 2.6.1 to enhance the user interface of the recommender systems by adding explanations so users can understand exactly what they have been recommended and why (Pu and Chen, 2007; Cremonesi et al, 2017). By explaining the rationale behind the recommendation of a specific training pathway, the system aims to build trust with the user and in turn increase their responsiveness to the recommendation. Another intentional design choice has been displaying the alternative training option for the user and why that choice was not suited to them. This allows for transparency between the system and the user so they can see the details of why the other option has not been selected for them. For example, as seen in Figure 13, a user who has been recommender a high severity intervention can see that they have been recommended an offline training pathway where they will benefit from hands-on support, networking, and an increase likelihood of completing the training session. However, with the online training pathway, these opportunities may not be available to them.

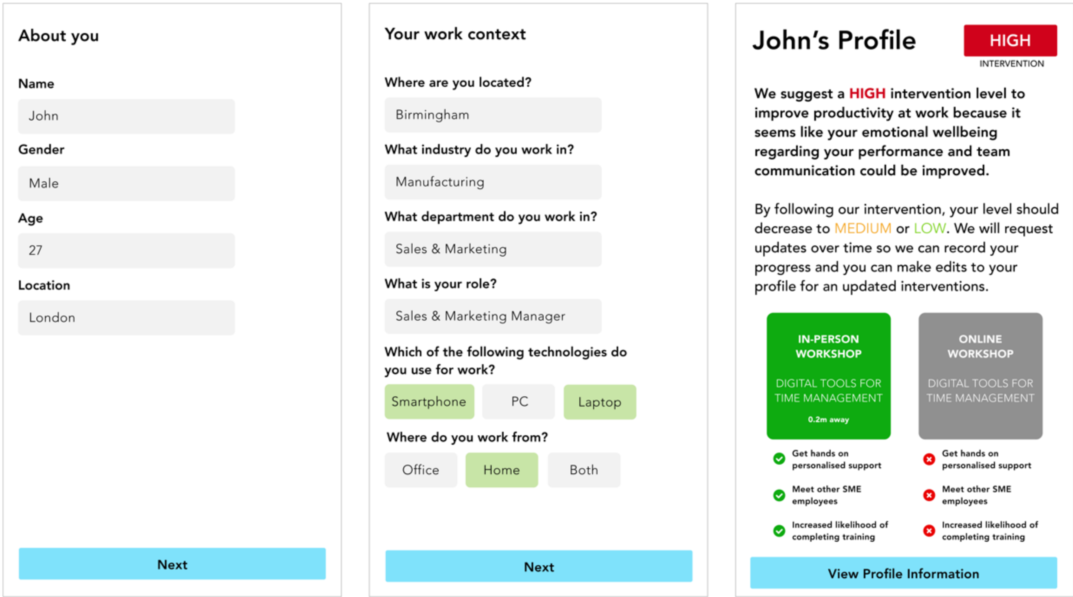


Figure 14: Wireframe of user intervention, demographics, and work context.

6.3 User-profile development using SMECAOnto

A number of user profiles have been developed using a NOSQL database. The profiles are constructed using the ontology design (SMECAOnto) in chapter 5 (see figure 10). Each user will have an appropriate intervention assigned to them based on the data provided. Refer to Appendix C to view a data model of the ontology in relation to the required data.

The NOSQL database being used to develop the user profiles is Firebase Realtime Database. Figure 15 is a screenshot of the data tree which displays one user profile that has been constructed using the SMECAOnto design. This provides SME-CARS input that consists of the relevant context needed to generate appropriate recommendations for the user.

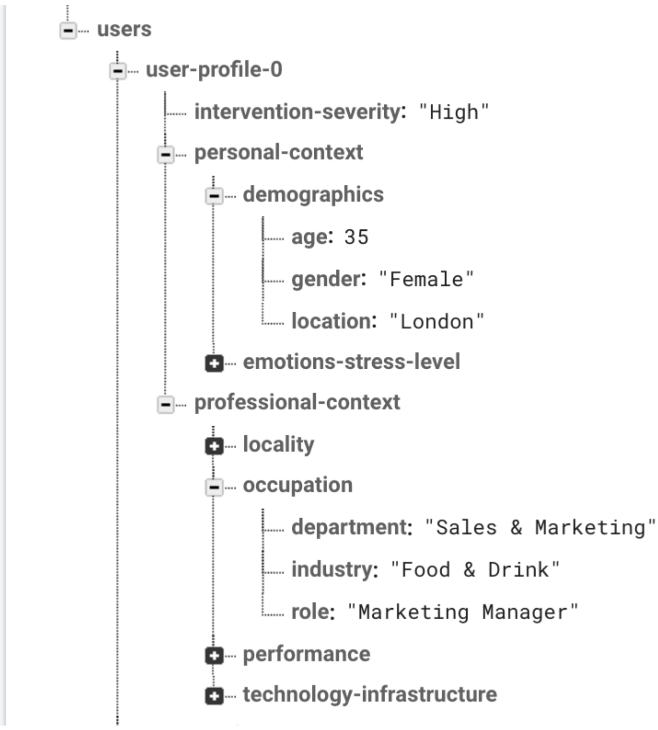


Figure 15: Example of user profile with ontology properties.

6.4 Digital tool training recommendations

The NOSQL approach is used again to develop a detailed list of training opportunities for each intervention type. There are three intervention severities that could be suggested to users based on their context. A brief overview of the output and the recommendation generation process can be seen in the following model (figure 16).

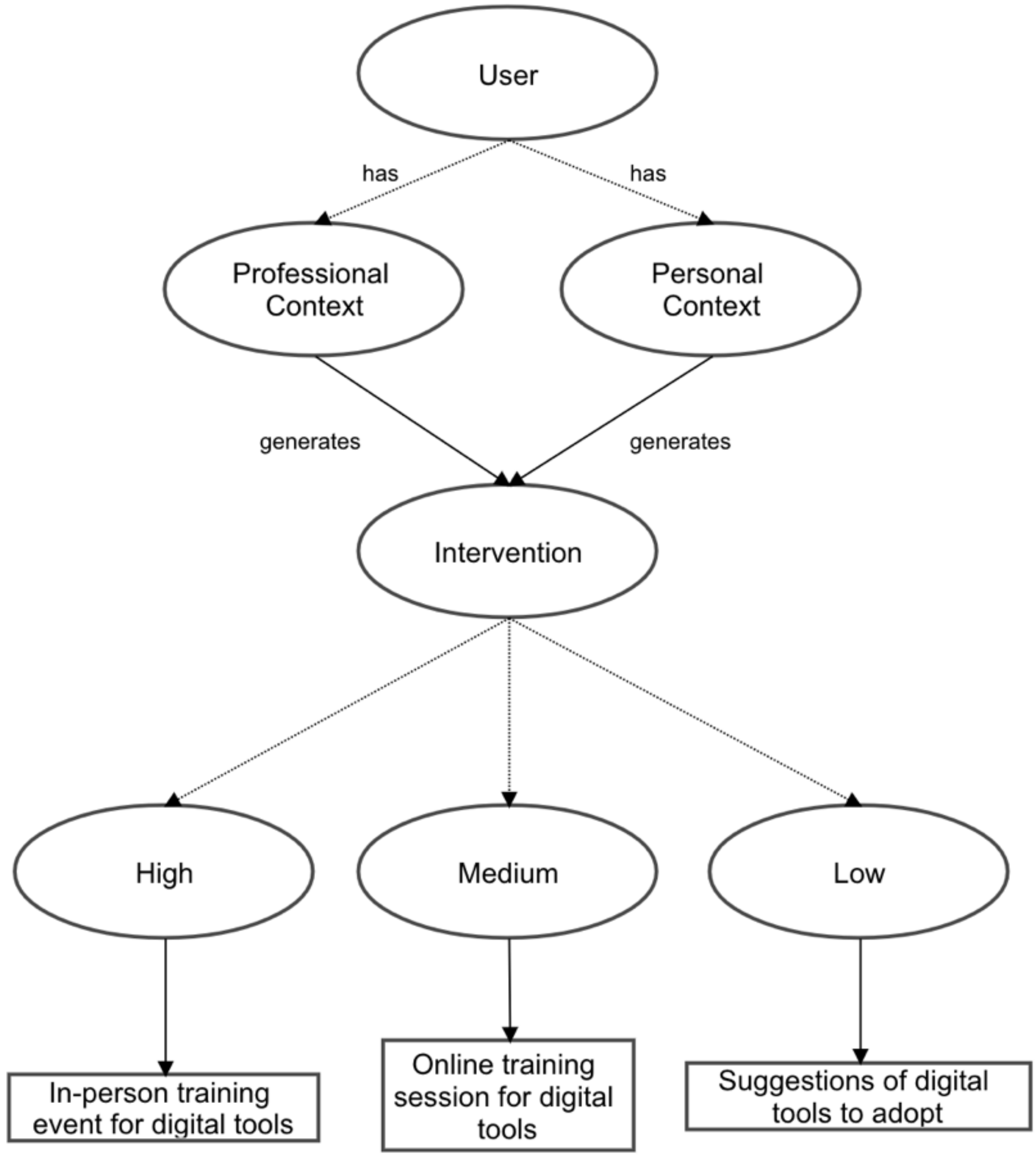


Figure 16: Model displaying three interventions: high, medium, and low.

Table 16 details the possible interventions and the user characteristics associated to each intervention. The results from the HeadsUp trial in Chapter 4 established that users were likely to complete more training if following the offline pathway (in-person) instead of the online pathway (digital). For this reason, users who require more immediate and hands-on training will be recommended a high severity intervention of offline training which they are more likely to complete. Additionally, users who do not require immediate help will be suggested a lower severity intervention of online training (medium severity) or a list of recommendations of online tools (low severity) as the need to complete training is less acute for them.

Intervention severity	User characteristics	Description of intervention
Low	In terms of personal context, this user's emotional wellbeing would be good. Their professional context would also be good as their actual performance would meet, exceed, or be close to their expected performance.	Suggestions of digital tools and supplementary materials to help the user's relevant business area.
Medium	For these users, either one of the contexts from personal or professional would be poor, and one would be good. For example, high stress levels, but meeting expected performance. Or both would be mediocre. E.g., medium stress levels, but actual performance 3 when expected performance is 5.	Online training for digital tools that help the user's business area. This type of training would consist of live sessions that would be attended virtually by users.
High	For these users both contexts would be poor. For example, high stress levels, and low actual performance compared to expected performance.	Offline training for digital tools that help the user's relevant business area. Offline training requires the user to attend workshops in person and receive more hands-on support.

Table 16: Intervention types and respective user characteristics.

Figure 17 displays the data tree for the interventions. They are broken down into four types of training to address respective problem areas: team communication, organisation, sales and marketing, and time management.

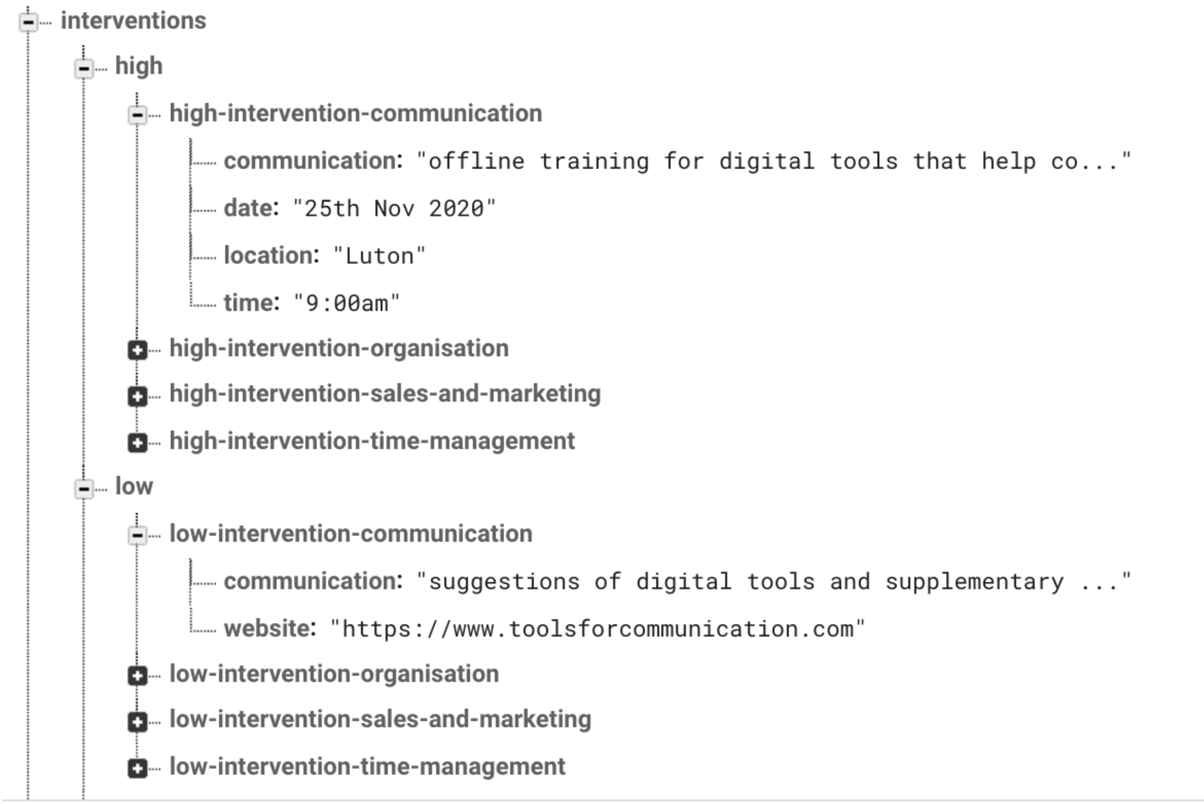


Figure 17: Data tree of the types of interventions

6.5 Querying Users

The data was moved from Firebase to AWS DynamoDB to run queries on it due to the ease of running queries on NOSQL data using the built-in console. Querying the database bridges the gap between SMECAOnto and SME-CARS by demonstrating how collecting data through the context model can be used to generate recommendations for user.

Querying the ontology helps surface users with specific characteristics (see figure 18). For example, users who have a stress level below 3 and their actual performance is greater than 3 would indicate that they are doing relatively well in managing their stress and are also performing well at work. These users would be assigned a low-severity intervention level. Medium and high severity levels would be assigned to users who are either performing lower than 4, have stress-levels that are greater than 2, or both.

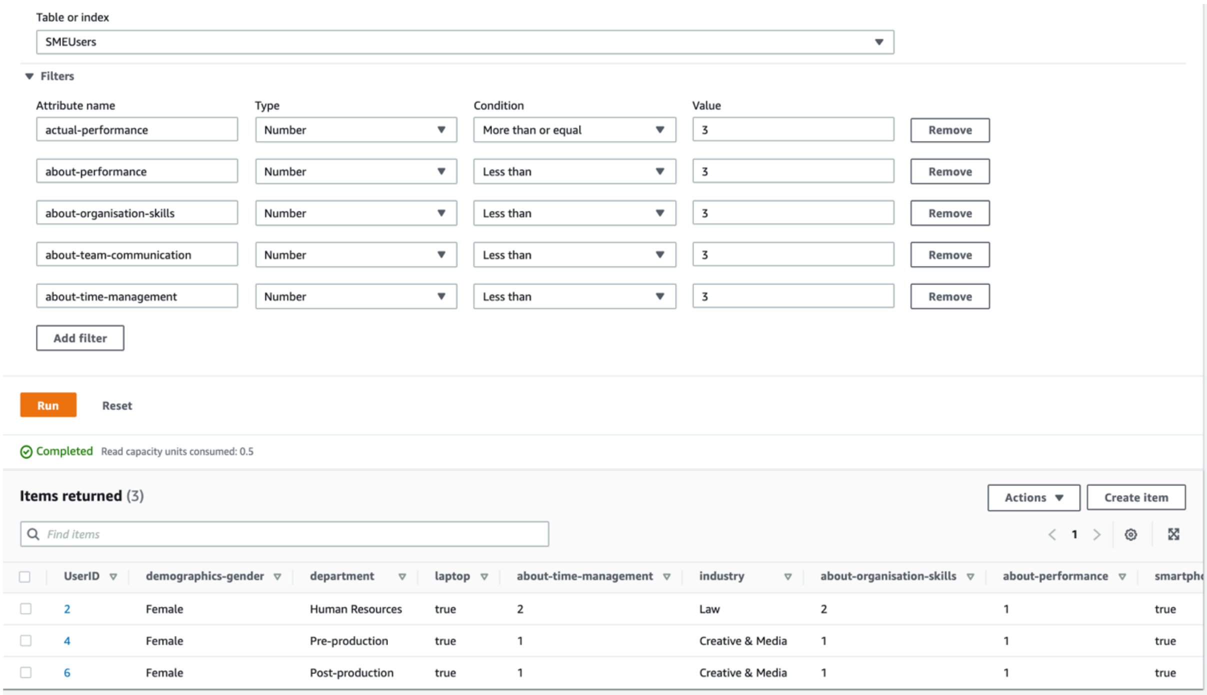


Figure 18: SMECAOnto being queried

6.6 SMECAOnto Evaluation

Evaluation is a core process within the Design Science Research (DSR) methodology, therefore, SMECAOnto requires evaluation to determine the effectiveness. Competency questions have often been used as a method of evaluating the quality of ontologies across various domains (Bezerra et al, 2013; Duque-Ramos et al, 2014; Gruninger and Fox, 1994). Competency questions have also been used to evaluate ontologies when using the

DSR methodology (Tebes et al, 2020). Through an extensive literature review, Chapter 2 determined information that would be useful to collect for the context model and generate user-focused recommendations. Competency questions will now be determined in order to test the effectiveness of SMECAOnto designed in chapter 5 (see figure 13).

6.6.1 Literature competency questions

Emotional context related competency questions

Collecting user emotions as a context piece when developing recommender systems is a fairly recent practice (Gonzalez et al, 2007). The results from this research concluded that emotional context makes an important contribution to context-aware recommender systems (ibid). Since then, there have been multiple pieces of research that establish the effectiveness of collecting user emotions as useful context pieces (Han et al, 2010; Odic et al, 2013; Tkalčič et al, 2011; Tkalčič et al, 2013). Additionally, Bellet et al (2019) found that happy employees are 13% more productive and additional research has found that negative emotions negatively impact productivity (Bui et al 2021). Therefore, SMECAOnto should be effective in collecting user emotions and factoring them into the recommendation process. The following competency questions will be used to determine if the ontology is effective in doing so:

1. How stressed is the user feeling about their performance at work?
2. How stressed is the user about their time-management skills at work?
3. How stressed is the user about their team communication skills at work?
4. How stressed is the user about their organisation skills at work?

Location context related competency questions

Several researchers have highlighted location as a useful context piece to collect when looking to generate recommendations for users. This has led to Location-Aware-Recommender Systems (LARS) emerging and garnering much attention in recent years (Rodríguez-Hernández et al, 2015; Villegas and Müller, 2010; Sarwat et al, 2014).

SMECAOnto gathers location as a context piece from users by collecting data about their home location, work location, and work environment. The following competency questions will be used to determine if it does so effectively:

1. What is the user's typical work environment?

Demographic related competency questions:

Demographical information can be used to enhance the quality of recommendations for users (Cano and Morisio, 2017; (Vozalis and Margaritis, 2003). For example, offline training which requires a person to be physically present could use information about where the user lives to recommend training the is local. Demographical information could also be used to assess the preferences of similar users and how they have responded to recommendations (Burke 2002; Sridevi & Rao, 2017; Ghazanfar & Prugel, 2010). By incorporating the collection of demographical data into SMECAOnto, it hopes to increase the effectiveness of recommendations.

The following competency questions will be used to determine whether SMECAOnto effectively collects relevant demographical data from users:

2. What is the user's age?
3. Where is the user located?
4. What is the user's gender?
5. What industry does the user work in?
6. What is the user's job role?
7. Which department does the user belong to?

6.6.2 Data competency questions

The next set of competency questions will be determined by using the findings from the SME research study Heads Up in Chapter 4. The descriptive statistics from the data found there was a variation in the retention rate for training of participants across industries. For this reason, SMECAOnto factors in the user's work context.

When analysing the data for statistical significance, a key finding showed there was statistical significance between a user's training pathway (intervention type) and meeting training compliance. Offline users who completed training in person were likely to complete more training than online participants who completed training virtually. For this reason, the ontology should determine the user's performance at work to identify their need for training. By doing so, the system can recommend interventions that would be beneficial for the user. The competency questions to measure performance would be:

1. How would the user rate their performance at work?

6.6.3 Testing SMECAOnto

This section uses the competency questions (CQ) to test SMECAOnto by querying the ontology. Table 17 presents satisfactory results from the CQ testing to show that the ontology can successfully classify user context. The implementation of SMECAOnto through SME-CARS may be able to increase digital tool adoption by effectively gathering user context and using it to recommend appropriate digital tool training to SME employees. This should lead to an increase in productivity among SMEs.

CQ	Answer	Correct?
How stressed is the user feeling about their performance at work?	4	Yes
How stressed is the user feeling about their time-management skills at work?	5	Yes
How stressed is the user feeling about their team communication skills at work?	3	Yes
How stressed is the user feeling about their organisation skills at work?	4	Yes
What is the user's typical work environment?	Remote	Yes
What is the user's age?	35	Yes
Where is the user located?	London	Yes
What is the user's gender?	Female	Yes

What industry does the user work in?	Food & Drink	Yes
What is the user's job role?	Marketing Manager	Yes
Which department does the user belong to?	Sales & Marketing	Yes
How would the user rate their performance at work?	2	Yes

Table 17: CQ Tests on SMECAOnto.

6.7 Summary

This chapter combines the findings and outcomes from chapter 2, 4, and 5 go demonstrate and evaluate the contribution in this research which is a crucial step in the DSR methodology (see sections 3.3.4 – 3.3.5). The developed ontology SMECAOnto has the capability to collect context from SME employees which can help determine their need for digital tool training. SME-CARS has implemented SMECAOnto in this chapter to demonstrate how employee context can be used in practice to determine an intervention level and recommend digital tool training for improved productivity. Section 6.2 developed a user-facing interface for SME-CARS which demonstrates how an SME employee would interact with a system utilising SMECAOnto to provide personal, professional, and emotional context. Section 6.3 used a NOSQL database to outline how data gathered using SMECAOnto is stored and used to construct user profiles. Section 6.4 used findings from Chapter 4 to define the training opportunities that will be recommended to users based on the data collected through SMECAOnto. The profiles have then been queried in section 6.5 to demonstrate how SMECAOnto categorises users and assigns intervention levels. Table 23 explained 3 interventions and the user characteristics that qualify users for each training pathway. Lastly, section 6.6 identified competency questions (CQ) using findings from literature in chapter 2 and the data from chapter 4 and used them to test SMECAOnto in section 6.6.3.

Chapter 7 Conclusion and Future Research

7.1 Overview

Chapter 7 concludes this paper by summarising the research and suggesting future work that could be done in the area.

7.2 will summarise the research. 7.3 will present the research contributions that have been made in this paper and section. Section 7.4 will assess the research objectives identified in chapter 1 to determine whether they have been met. 7.5 will underline the any limitations that may exist. Finally, section 7.6 will suggest future direction which can be taken in this area of research.

7.2 Research Summary

It has been established that SMEs in the UK suffer from low productivity levels which is a leading cause of failure for many of them. The UK has also performed poorly in terms of labour productivity growth. Digital tools have been found as mean to improving productivity and SMEs have been encouraged to adopt these tools for their business activities. However, providing SMEs training of such tools is crucial in order to educate users and ensure that they are fully aware of how to use the tools as intended.

Recommender systems are used widely today in markets such as retail, e-commerce, entertainment, and more for several purposes. There are a variety of recommender systems available, with increased research introducing many state-of-the-art systems to the space. Context-aware recommender systems (CARS) are one of the more recent contributions to the field of recommender systems which focus on collecting and utilising user context to generate recommendations for the user. Such systems present an opportunity to improve recommendation quality by learning about SMEs and their employees in order to recommend interventions that are personalised to their needs. The data input is crucial to the development of context-aware systems but there is no standardised way to collect and organise context due to the how much the context varies across domains. Ontologies have been found to be the most expressive context models due to their ability to effectively display relationships when defining context and develop a shared understanding around a domain.

Due to the lack of research at the intersection of SME employee productivity and recommender systems, a context model which builds a shared understanding around the factors that impact SME productivity is needed. Additionally, the large availability of digital tools which is increasing rapidly coupled with the need for digital tool training creates a gap for a process that helps guide SME employees to appropriate digital tools according to their needs. Consequently, this thesis has sought to assist SMEs and those interested in improving labour performance at SMEs learn about employee context. This aim was achieved by developing an ontology (SMECAOnto) that collects relevant data from SME employees that can be analysed to learn more about how they can be supported. SMECAOnto has then been implemented through SME-CARS in order to demonstrate how it could be used in practice to recommend digital tool training that helps SME employees effectively adopt these tools and improve productivity. The following objectives were identified in Chapter 1 to help guide the research:

Objective 1: Analyse appropriate literature to build a knowledge base of traditional and state-of-the-art recommender systems that consider user-context.

Objective 2: Investigate the condition of SMEs, their relationship with digital tools for business practices, and their journey towards digital tool adoption.

Objective 3: Identify requirements for a context model that would be applied to a recommender system for the SME environment (taking into consideration the findings from Objective 1 and Objective 2).

Objective 4: Develop a model (SMECAOnto) that satisfies the requirements generated for Objective 3 and gathers appropriate user context.

Objective 5: Demonstrate the model through an instantiation (SME-CARS) and evaluate the effectiveness of the model using competency questions.

Chapter 2 presented a literature review that explored the SME environment in the UK and SME relationship with productivity. Doing so provided information on the pressing problems within SMEs including that of low productivity levels. Literature also underlined the potential for digital tools to improve SME productivity. However, there was an emphasis on the need for SMEs to ensure they are equipped with the appropriate resources and capabilities needed for such digital tools (e.g. via training), rather than simply acquiring digital platforms. Chapter 2 also critically reviewed the various traditional and state-of-the-art recommender systems available today. This helped build a knowledge base around the types of recommendations that can be generated by such systems whilst considering their effectiveness. Through the research, context-aware recommender systems (CARS) were uncovered. One of the more recent contributions to the CARS space is a system called Interactive Context-Aware Recommender System (I-CARS) which directly collects context from the user in order to generate relevant recommendations. These findings led to a deeper understanding of the productivity problem among SMEs and how recommender systems could be leveraged to help SMEs improve productivity. In doing so, chapter 2 was able to meet objectives 1 and 2.

Chapter 3 selected Design Science Research as the chosen methodology being followed for the research conducted in this thesis. The chapter outlined how objectives would be achieved by using Design Science Research. The main artefact developed was an ontology-based context model (SMECAOnto) that can be used to gather appropriate context from SME employees. The second artefact was SME-CARS – an instantiation that implements SMECAOnto to collect employee context and generate recommendations.

Chapter 4 analysed the data collected from the Heads-Up Trial conducted by Brunel University London in partnership with Enterprise Nation which followed SMEs on their journey towards productivity through digital tool training and adoption. The analysis provided a deeper understanding of how SMEs interact with training and digital tools to outline key findings. These findings contributed to the design of the context-aware recommender system SME-CARS, particularly the output of the recommender system. The research in chapter 4 contributed to meeting objective 2.

Chapter 5 considered the findings from literature (see chapter 2) and data analysis (see chapter 4) and presented various design suggestions through the form of wireframes. Ultimately, one design suggestion was selected for development. State-of-the-art recommender system I-CARS was chosen as the system being extended for the SME environment in the form of SME-CARS. Requirements were identified for SMECAOnto and it was then designed as the ontology-based context model for SME-CARS. As a result, this chapter 5 met objectives 3 and 4.

Chapter 6 developed SMECAOnto for SME-CARS using a NOSQL database. The ontology was queried so it could be evaluated against competency questions. In doing so, objective 5 was met.

7.3 Research Objectives Evaluation

Table 18 evaluates the research objectives and highlights the outcome of each as well as where in the paper they have been met.

Objective	Description	Chapter	Outcome
1	Analyse appropriate literature to build a knowledge base of traditional and state-of-the-art recommender systems that consider user-context.	2	Literature view on recommender systems found context-aware recommender systems (CARS) effective in generating high quality recommendations by collecting user context. I-CARS was found to effectively gather context directly from users to learn about their needs and generate recommendations (see section 2.4-2.6).

			Ontologies were found to be the most expressive context models for such systems due to their ability to define relationships and build a shared understanding around a domain (see section 2.6.6).
2	Investigate the condition of SMEs, their relationship with digital tools for business practices, and their journey towards tool adoption.	2 and 4	A literature review explored the relationship of SMEs with productivity and online tools (see section 2.2-2.3). Adopting digital tools can help improve productivity, however, SMEs must be educated on how to use the tools effectively. The data from a research study by Brunel University London in partnership with Enterprise Nation was analysed for key findings about the SME relationship with training, online tools, and productivity. Sections 4.4-4.5 found offline (in-person) training to have a lower drop off rate compared to online (virtual) training and that digital tools could lead to increased productivity for participants who undertook training.
3	Identify requirements and design a context model that would be applied to a recommender system for the SME environment (taking into consideration the findings from Objective 1 and Objective 2).	5	Requirements for the ontology-based context model were identified and multiple designs of how the recommender system would work in practice with such a model were proposed. A design which extended I-CARS to interactively gather professional, personal, and emotional context was selected for further development (see section 5.5).
4	Develop a model that satisfies the requirements generated	5	SMECAOnto was developed using a NOSQL database and detailed wireframes

	for Objective 3 to gather appropriate user context.		were developed showing possible implementation (see section 6.2-6.3).
5	Demonstrate the model through an instantiation (SME-CARS) and evaluate the effectiveness of the model using competency questions.	6	This requirement was fulfilled by proposing SME-CARS which implemented SMECAOnto (see section 6.5). SMECAOnto was then queried in section 6.6.3 to test the ontology using competency questions.

Table 18: Evaluation of whether objectives have been met.

7.4 Research Contributions

This paper has followed the design science research (DSR) methodology to propose a solution for the low productivity levels among SMEs in the UK (March, Smith 1995, Peffers et al. 2007, Vaishnavi, Kuechler 2007, Hevner et al. 2004). Contributions for the DSR methodology are artefacts which can take the form of a model, method, and/or an instantiation. The key research contribution made in this paper is an ontology-based context model that collects information from SME employees to better understand their professional, personal, and emotional context. The following contribution is an instantiation: SME-CARS - an SME focused context-aware recommender system which implements SMECAOnto.

Contribution 1: Model - SMECAOnto

SMECAOnto is an ontology-based context model and the key contribution made in this paper. It is the foundation of SME-CARS and establishes the context being collected from

SME employees to understand them better. SMECAOnto collects and organises the input data of SME-CARS and therefore plays a crucial role in defining the output of the system. There are currently no ontologies catered to the SME domain which focus gathering context from SME employees to understand how they can improve productivity. Aguilar et al's (2018) CAMeOnto has presented a general ontology with the aim that it can be used across different domains, however, determining the relationship between SME employees and productivity requires a more specific ontology. While many dimensions from CAMeOnto are relevant to the SME domain, the grouping of context requires changes. CAMeOnto categorises context into internal, external, and boundary, however, SME-CARS categorises context based on personal and professional context. This structure allows for internal and external context to intersect, for example, user location and user emotions are both personal context in SMECAOnto. However, according CAMeOnto, location would be external, and emotions would be internal. The proposed ontology in this paper (SMECAOnto) addresses this contradiction. Additionally, SMECAOnto introduces emotions as a core dimension of the ontology due to the impact emotions have on productivity (Bui et al, 2021; Bellet et al, 2019). Whilst there have been many ontologies proposed that focus on gathering domain specific context, none have focused on gathering context which helps determine the relationship between SME employees and productivity.

Contribution 2: Instantiation – SME-CARS

SME-CARS is context-aware recommender system specialised for the SME domain. The system interacts directly with SME employees in order to identify their needs and recommend relevant digital tool training. Research in section 2.2 identified the ability digital tools have to increase productivity among SMEs. However, it also revealed a need for the facilitation of digital tool training to ensure such tools are adopted effectively. Findings in chapter 4 built an understanding of the SME employee journey towards digital tool training and uptake. This helped inform requirements for SME-CARS. SME-CARS extends I-CARS proposed by Lumbantoruan et al (2019) by using the same interactive approach of gathering context from the user, however, it focuses more on the emotional wellbeing of SME employees and their performance in order to make recommendations.

Whilst recommender systems have been proposed for SMEs previously, they have focused on boosting customer experience and retention to create business value (Portinale and Brondolin, 2021; Lee et al, 2021; Beel et al, 2019). Limited research has been devoted to exploring the application of recommender systems for the purpose of improving internal practices at SMEs and boosting productivity. Ahmed and Nanath (2021) designed a recommender system that addressed rising cyber-attacks on SMEs and proposed a system that recommends cybersecurity solutions. Darzi et al (2010) is the only research found which shares similarities with the aim of this paper and focuses on suggesting training to SMEs to build skills and boost productivity. Darzi et al (2010) combined fuzzy logic and case-based reasoning to propose FCRS - a hybrid recommender system which focuses on training course recommendations for SME employees to fill skill gaps and increase productivity. However, FCRS generates recommendations based on information provided by the SME as a whole rather than assessing the individual needs of each employee. There has also been a rapid increase in the number of digital tools available since this contribution and research addressing the use of such tools for productivity at SMEs is a recent focus in the field (OECD 2019; Cenamor et al, 2019; Roland, 2018; Attaran et al, 2019; OECD 2021). As outlined in Table 6, there is a positive relationship between digital tools and productivity, however, digital tool adoption is low among SMEs. This has created a gap in the SME and recommender system space for contributions like that being made in this paper - a system that aims to boost productivity of SMEs by leveraging recommender systems to increase uptake of digital tools. SME-CARS is the first recommender system to address internal practices of individual SME employees with the aim of boosting productivity through digital tool training and uptake.

The usage of SMECAOnto enables the development of a system like SME-CARS which can effectively gather relevant context from SME employees to assess their mental wellbeing and workload. This allows the system to identify a training pathway that supports the adoption of digital tools. The system would guide employees through the journey towards productivity by not only assessing their working environment but suggesting the most appropriate route they can take to effectively adopt online tools. Furthermore, it could help employers understand more about mental wellbeing and workload of their employees which plays a significant role towards their productivity.

The contribution made in this paper would be of use to; SMEs, government, implementers, technology companies, training organisations, business consultants, and analysts working to study or improve the productivity of SMEs and uptake of digital tools.

7.5 Research Limitations

Whilst the research in this paper has made valuable contributions to the SME environment regarding their journey towards productivity, it is important to consider the limitations and challenges faced.

Context-aware recommender systems are considered a more recent variation of recommender systems compared to traditional systems like those using content-based or collaborative-filtering approaches. For this reason, the depth of research available around CARS is not as vast as traditional systems. The complexity and broadness of 'user context' which is the input for a context-aware system has made it difficult to adopt a standardised approach towards development (Sassi et al, 2017; Raza and Ding, 2019). Such systems also require more data to be collected in order to generate recommendations which means that the quantity of data needed is higher than traditional systems. This coupled with the need for high quality data like context which is already difficult to model are some of the factors which have led to there being less research in the area to date (see section 2.6.5).

Another limitation faced during the research was the quality of data collected through the Heads-Up trial. The number of participants who went on to book training after completing the baseline was low which led to limited data. There were also many participants who had to be excluded from the trial which further reduced the sample size. Retention rates were also extremely low with participants dropping off at various stages of the trial for reasons unrelated to the training (e.g., technical issues). However, analysis was done to draw descriptive statistics and statistical significance. In some cases, two tests were done to validate significance due to the small sample size.

7.6 Future Research Direction and Recommendations

The research has much room for growth to enhance the quality of recommendations being generated by the system. The areas for growth include:

1. Measuring productivity – Collecting more concrete performance statistics from employees or managers related to productivity/performance before training would help identify areas where digital tools may be able to help more accurately by corroborating employee perception with actual performance. Such data collected after the implementation of digital tools would also allow the system to better measure impact and generate more robust recommendations over time.
2. Increased focus on SME employee emotions – The research touched on the impact emotions have on productivity in the workplace. Using SMECAOnto to focus on the 'emotions' dimension could lead to more research on how emotions impact productivity and factors that contribute towards positive or negative emotions. Due to the fluctuating nature of emotions, there is much research that could be done in this area to explore how something so dynamic could be measured and improved in relation to work and productivity.

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Appendices

Appendix A

t-Test: Paired Two Sample for Means (Offline) – Time spent on business activities by offline participants after training

	Pre-T	*Post-T*
Mean	24	19
Variance	263.6	191.6
Observations	6	6
Pearson Correlation	-0.0676353	
Hypothesized Mean Difference	0	
df	5	
t Stat	0.55578432	
P(T<=t) one-tail	0.3011547	
t Critical one-tail	2.01504837	
P(T<=t) two-tail	0.6023094	
t Critical two-tail	2.57058184	

Appendix B

t-Test: Paired Two Sample for Means (Online) – Time spent on business activities by online participants after training - Statistically significant

	Pre-T	*Post-T*
Mean	21	28.4333333
Variance	163	339.030952
Observations	15	15
Pearson Correlation	0.83315525	
Hypothesized Mean Difference	0	
df	14	
t Stat	-2.7409977	
P(T<=t) one-tail	0.00796196	
t Critical one-tail	1.76131014	
P(T<=t) two-tail	0.01592392	
t Critical two-tail	2.14478669	

Appendix C

Data model of SMECAOnto in relation to SME-CARS.