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"The Impact of a Hybrid Customer Support Model on Customer Satisfaction in the Software Industry: A Qualitative Study of Customer Support Experiences at AFAS"

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Abstract

The purpose of the study is to investigate the impact of a hybrid customer support model on customer satisfaction in the software industry. Using a qualitative case study approach at AFAS Software, the research examines how customers value the interplay between AI-based tools and human support agents. Data was collected through an analysis of feedback logs and semi-structured interviews with customers of AFAS. There was a focus on five central themes of customer satisfaction: speed of resolution, correctness of solution, feeling understood, customer effort, and seamless transition. The combination of this empirical research with a literature review on this theme showed that while the hybrid model improves efficiency and provides 24/7 accessibility for simple issues, it often increases customer effort and fails to meet expectations for complex problems. In particular, differences emerged between more experienced customers – those familiar with the software and support process – and inexperienced customers with limited prior interaction. Experienced customers found the AI interaction cumbersome and preferred immediate escalation to human support for complex problems, inexperienced customers generally appreciated the clarity and structured path offered by the AI for simple queries. This contrast is particularly relevant in the software industry, which compared to other industries is known for its highly diverse customer base with different levels of experience in seeking support and their software knowledge. The research highlights the importance of balancing AI automation with human empathy and understanding of context, and emphasises that a hybrid model that caters to all may not fully meet the needs of different customers.

Preface

This thesis marks the final requirement for completing the Master's program in Strategic Management at Tilburg University. It represents the outcome of an intensive, yet enriching period in which I explored the impact of artificial intelligence (AI) on customer support practices within organisations. My motivation for this topic stems from a strong interest in how technological innovations not only transform internal processes but also shape the direct interaction between companies and their customers. This study focuses on how customers with different levels of experience perceive the hybrid support model implemented at AFAS Software, a model in which AI plays a central role in the initial stages of service delivery. Combining academic theory with a real-world case enabled me to analyse an emerging phenomenon while generating insights relevant to companies navigating digital transformation.

I would like to thank my thesis supervisor Gerwin van der Laan for his valuable feedback, constructive questions, and consistent support throughout the research process. My sincere thanks also go to AFAS Software for making this research possible. In particular, I would like to thank Sven de Zeeuw, Customer Support Manager at AFAS, for his involvement, openness, and practical support during the development and execution of this study.
Finally, I am grateful to my family and friends for their encouragement, interest and support, especially during the more demanding phases of this project. Writing this thesis has been both an academic and personal learning experience. It has challenged me to independently conduct research and connect theoretical models with practice. I look back on this process with pride and hope that the insights generated may contribute to the conversation on how organisations can strategically deploy AI to improve customer support while accounting for differences in customer experience.

Tilburg, June 2025

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1. Introduction

AFAS is a software company with more than 12,000 customers, spanning every sector in the Netherlands. Every day, organisations rely on AFAS for their administration, HR processes, and business operations. When something goes wrong, AFAS's customer support department, the vital link between customers and software, is ready to help. However, when AI gradually replaces the traditional human helpdesk, it raises important questions about customer satisfaction. In early 2025, AFAS introduced AI-powered tools to automate the inflow of basic customer questions. The goal was faster responses, reduced pressure on employees, and more time for handling complex issues. A logical step in an era where efficiency and scalability are increasingly crucial. And the initial results are promising, the number of incoming incidents has clearly declined. However, could there be a downside to this innovation? How do customers experience the shift from human to machine? Do they still feel heard, helped, and understood, or alienated by the standardised nature of the interaction? This thesis places that tension at the heart of its investigation. It explores the impact of AI-assisted customer support on customer satisfaction at AFAS and examines how technology and human service can be combined in such a way that both efficiency and customer-centricity are preserved.

1.1 Importance of Customer Satisfaction

Customer satisfaction has been an important topic in the literature for decades, as it is closely related to customer loyalty and business outcomes (Anderson & Sullivan, 1993; Williams & Naumann, 2011). Research suggests that elements such as product quality and price perception play a vital role in shaping satisfaction (Zeithaml, 1988).

However, to ensure customer satisfaction structurally, companies need to look beyond individual contact moments. Rawson et al. (2013) argue that this requires fundamental changes in organisational culture, performance indicators, internal collaboration, and process design, across the entire customer journey. In today's business environment, characterised by intense competition and a rapidly evolving business landscape, customer satisfaction has become a strategic focal point for companies striving for a sustainable competitive advantage (Hidayat et al., 2024). In a comprehensive meta-analysis of 245 empirical studies conducted over a 40-year period, Mittal et al. (2023) demonstrate that customer satisfaction is a key driver of both customer-level outcomes, such as retention, word-of-mouth, spending, and firm-level financial performance. Their findings also show that the strength of these relationships varies significantly depending on contextual factors, including industry sector, product type, and geographic region.

To realise these benefits, a generic or segmented customer approach is insufficient. Organisations need to develop a deep and holistic understanding of customer behaviour, preferences, and experiences throughout the customer journey. Lemon and Verhoef (2016) highlight that such insights come from combining customer data, interactions across multiple channels, and understanding the context in which these interactions take place. These insights form the basis for effectively tailoring services and communications to customers' specific needs and expectations. This approach allows companies to refine their service design, customer interactions and even product innovation, leading to stronger emotional engagement, and long-term customer loyalty (Lemon & Verhoef, 2016). A company's long-term success relies on its ability to attract new customers and maintain relationships with existing ones: an effort that demands a timely understanding of customer expectations and structurally exceeding them through meaningful, personalised interactions that foster loyalty and trust (Reinartz & Kumar, 2002).

1.2 Impact on Customer Support

Customer support encompasses a wide range of services that organisations use to effectively support customers in using their products or services. This support extends beyond just after-sales care: it is interwoven throughout the entire customer journey and thus influences both the customer experience and brand perception. According to Goffin and New (2001), effective customer support already starts in the design phase of a product. By incorporating support requirements directly into the design, a better connection is created with the needs of customers, which promotes customer-oriented innovation.

When customer support is deployed in a consistent, empathetic, and proactive manner, it contributes to higher customer satisfaction and trust in the brand. Research shows that clear communication and customer involvement in service provision is strongly related to customer loyalty (Maghembe & Magasi, 2024; Masoudinezhad, 2018). Even when something goes wrong, such as a delayed delivery or a defective product, a quick and appropriate response can make all the difference, customers often experience such moments as proof of reliability (Lu et al., 2020).

Over time, customer support has evolved from a reactive, operational function to a strategic pillar that contributes to competitive advantage and customer value (Sheth et al., 2020). Because of this strategic role, it is essential that organisations carefully align distribution channels with industry-specific requirements. The effectiveness of customer support depends strongly on both how it is offered and the context in which it is provided (Goffin, 1999).

1.3 Integration of Artificial Intelligence in Customer Support

AI in the context of customer support, is according to Xu et al., (2020) defined "as a technology-enabled system for evaluating real-time service scenarios using data collected from digital and/or physical sources in order to provide personalised recommendations, alternatives, and solutions to customers' enquiries or problems, even very complex ones" (p.1).

More organisations are integrating artificial intelligence (AI) into their customer support to both increase efficiency and reduce operational costs. Empirical research shows that AI technologies such as chatbots, IVR systems, and predictive analytics lead to shorter handling times and lower staff costs (Konda, 2025; Singh, 2025b). A study on the ROI of AI integrations shows that an initial investment of $500,000 and annual operational costs of $100,000 resulted in annual savings of $800,000 and $300,000 in additional revenue through customer retention. This yielded a first-year return of 83.33% (Katragadda, 2024). These findings confirm that AI in customer support not only improves service but is also a powerful lever for cost savings and growth. Research shows that these applications not only increase efficiency but also contribute to a decrease in complaints and better service experiences, especially for simple issues (Adam et al., 2020; Singh, 2025b). This allows human agents to focus on more complex or sensitive issues, while the AI system continuously learns from previous interactions and adapts accordingly. While AI applications in support can deliver both cost benefits and improved customer experiences, this research focuses primarily on the impact on customer satisfaction. Cost savings are seen as an important context, but customer satisfaction is central.

In addition to automation, AI also contributes to an improved customer experience through data-driven personalization. By leveraging customer data and predictive algorithms, AI systems can tailor interactions and offerings to individual needs (Chen & Prentice, 2024). AI-integrated CRM systems streamline customer interactions and improve service consistency

(Ozay et al., 2024). Deploying AI in customer support also has obvious challenges. An often-cited concern is the limited ability of AI to mimic nuanced human interactions. Research by Hill et al. (2015) shows that customers often perceive AI-driven assistance as emotionally distant, which can lead to a less positive perception of service quality. In addition, inaccuracies in speech recognition or the inability to adequately handle complex requests can lead to frustration and the need to involve a human agent (Ozuem et al., 2025). These limitations underscore the importance of a hybrid approach, in which AI takes on standardised tasks while human support remains available for more nuanced interaction. While AI has great potential to improve customer support, its success depends on careful implementation. Organisations must strike a balance between efficiency and empathy, leveraging the power of AI without losing sight of the human element that remains essential to customer satisfaction.

1.4 Empirical Research at AFAS

AFAS Software is a Dutch family-owned enterprise specializing in the development of business software aimed at automating administrative processes. Its product suite includes integrated solutions for HRM, payroll, finance, project management, CRM, ERP, and other core business functions. AFAS focuses mainly on small and medium-sized enterprises, non-profit organisations, and educational institutions. Their software helps organisations work more efficiently by digitizing processes and managing data centrally.

AFAS uses a hybrid customer support approach that combines AI with human interaction. Technologies such as chatbots and smart knowledge bases are used to automatically answer simple questions, while more complex or sensitive issues are forwarded to human support staff. This method is aimed at combining speed and efficiency with empathy and personal attention. An important feature of the support process at AFAS is that all customers, regardless of their segment or type of question, are helped via the same digital channel. Each customer goes through the same first steps: an AI-driven chatbot or search function first tries to solve the problem independently, for example by offering automatically generated help articles via AI. Only if the problem is not solved in this way, support from an employee follows. AFAS has been applying these AI applications since January 2025, which means that little is known about the impact of this implementation on customer satisfaction or about differences in perception between customer groups. This is relevant, as AFAS serves a diverse customer base with varying levels of software knowledge and digital experience. It is precisely these differences that can influence how customers experience hybrid customer support. The uniform support process makes AFAS a particularly suitable case to investigate how different customer groups value this hybrid support model and to what extent their satisfaction is influenced by the nature of their question. Because all customers go through the same path, observed differences in satisfaction can be attributed to the complexity of the customer question rather than to variation in the support process itself.

1.5 Literature Gap

Although extensive research has been conducted on the use of artificial intelligence (AI) in customer support, such as chatbots and virtual assistants (Nicolescu & Tudorache, 2022), the literature often focuses on standard applications in generic sectors. Recent studies, including those by Leocádio et al. (2024) and Inavolu (2024), highlight how hybrid models, where AI systems collaborate with human workers, can improve the efficiency and effectiveness of customer support. Yet the software industry remains underexposed in this debate, even though it has unique challenges. Software products are typically complex, updates follow each other in rapid succession, and the customer base is highly diverse in technical knowledge (Buxmann et al., 2012).

Existing research shows that AI is particularly suitable for handling simple and structured queries but proves less effective for more complex problems that require interpretation, empathy, or contextual understanding (Hill et al., 2015; Liu-Thompkins et al., 2022). This distinction is particularly relevant in software companies, where the nature of the help request can vary greatly depending on the experience level of the customer. Inexperienced customers are more likely to turn to support for basic usage questions, while more experienced customers submit queries that require deeper technical knowledge or product integration. Although some studies, such as those by Banerjee et al. (2023) and Wiethof and Bittner (2022), acknowledge that the effectiveness of AI-human collaboration is highly context-dependent, there is as yet hardly any explicit research on how customers with different experience levels value this hybrid support. This is remarkable given that software companies operate in a knowledge-intensive environment where customer satisfaction is partly determined by the extent to which the support provided matches the customers’ knowledge level and expectations (Rajala & Westerlund, 2007). Although Khan and Iqbal (2020) make general links between AI and customer satisfaction, they do not consider differences between experienced and inexperienced customers.

Thus, there is a clear gap in the literature regarding how hybrid AI-supported customer systems within software companies can respond to differences in customer experience. Given the inherent complexity and dynamism of the industry, the need for flexible and intelligent services has become a key focus of future research.

1.6 Problem Statement

Companies like AFAS are integrating AI into their customer support process, but it is unclear to what extent this hybrid approach matches key customer satisfaction factors. It is not known whether experienced customers react differently from inexperienced customers.
Given this context and the identified challenges, this research focuses on the following problem statement:

"To what extent does a hybrid customer support model align with the factors that software customers consider most important, and do these factors differ between experienced and inexperienced customers?"

By addressing this problem, the study aims to determine if the level of expertise of customers influences customer satisfaction in a hybrid (human/AI) support model.
Note: In this research conducted at AFAS, the two groups are distinguished from each other as follows.
Experienced customers: Functions as the main AFAS contact for more than five years and submitted mainly complex, configuration-related issues (with less than 10% classified as knowledge-based or user questions),
Inexperienced customers: Functions in this role for less than five years and had submitted at least 20% knowledge-based or simple user questions.

1.7 Research questions

Based on the problem statement, this research formulates one main question and several sub-questions. The research questions are divided into theoretical research questions and an empirical research question. In the literature review (Chapter 2), the theoretical questions are addressed, and in the Findings (Chapter 4), the empirical question will be answered. The literature review was based almost exclusively on peer-reviewed academic articles, and the empirical research was answered by analysing feedback logs and conducting qualitative interviews with AFAS' customers.

Theoretical research questions

- How is customer satisfaction conceptualised and measured in the context of hybrid AI–human customer support?
- What are important factors contributing to technology acceptance?
- What factors influence perceived service quality and satisfaction in AI-supported customer support according to existing literature?
- How do the distinctive characteristics of the software industry affect the design and perceived effectiveness of hybrid customer support?

Empirical research question

- How do different customer segments (experienced vs. inexperienced) perceive the AI implementations in AFAS' hybrid customer support, and how does this affect their overall satisfaction?

2. Literature review

2.1 Conceptualising Customer Satisfaction

Customer satisfaction is a core concept within service delivery and is the central outcome variable in this study. This section examines how customer satisfaction is defined in the literature and in what ways it is traditionally measured, particularly in service delivery contexts. Subsequently, the limitations of this model are discussed to get a better understanding to what extent it is applicable to current research.

2.1.1 Definition of Customer Satisfaction

Customer satisfaction is a central concept in marketing and service research. Over time, its definition has undergone significant changes. While early perspectives focused primarily on rational comparisons between expectations and actual outcomes, more recent approaches have expanded to include emotions, personal experiences, and the broader context in which the service or product is consumed.

One of the earliest academic contributions was made by Cardozo (1965), who found that customers could sometimes be more satisfied when they invested more effort in the purchasing process. Swan and Combs (1976) later described satisfaction as a personal judgment about whether expectations were met. Their conceptual work laid the foundation for the expectation-disconfirmation model, which was formalised by Oliver (1980). In this model, satisfaction results from the comparison between what a customer expects and what is experienced. This framework was further refined by Churchill and Surprenant (1982), who showed that expectations, perceived performance, and the degree of disconfirmation all contribute to the satisfaction outcome. While these cognitive models dominated early research, subsequent studies pointed out that satisfaction does not arise from a single transaction but develops over time. Johnson, Anderson, and Fornell (1995) emphasised that satisfaction is a cumulative process, shaped by prior experiences and the adjustment of expectations over time. In the 1990s, researchers began to pay more attention to the emotional aspects of satisfaction. Westbrook and Oliver (1991) demonstrated that emotional responses experienced during product use significantly influence how satisfied a customer feels. Their work marked a shift away from purely cognitive interpretations by showing that satisfaction is also shaped by affective reactions.

Building on this development, Giese and Cote (2000) proposed a widely cited conceptual definition of customer satisfaction. They described it as a short-lived emotional response that occurs at a specific time and is directed at particular aspects of the product acquisition or consumption experience. In their view, satisfaction is not a fixed attitude or general state, but a context-dependent response. Unlike earlier definitions, their framework also emphasised the importance of conceptual clarity and empirical testability to improve the precision and usefulness of the satisfaction construct in academic research.

In summary, the understanding of customer satisfaction has evolved from a simple cognitive comparison model to a more complex and multidimensional concept. Today, it is widely accepted that satisfaction involves both rational and emotional evaluations, develops over time, and is shaped by the specific context in which the customer experience takes place.

2.1.2 Traditional Measurement Approach

The SERVQUAL model, developed by Parasuraman et al. (1988), remains one of the most widely used frameworks for evaluating service quality. It defines service quality as the gap between what customers expect and what they actually experience, a concept often described in terms of the difference between expectations and perceptions. While the model was initially created to measure service quality, several studies have confirmed that perceived service quality significantly affects customer satisfaction (Mahamad and Ramayah, 2010; Oh, 1999).

SERVQUAL breaks service quality down into five main dimensions. Tangibles refer to physical elements like facilities, equipment, and overall appearance. Reliability describes the ability to deliver the promised service dependably and accurately. Responsiveness is about the willingness of staff to help customers and respond to their needs promptly. Assurance relates to the professionalism, courtesy, and knowledge of employees, and how well they build customer confidence. Finally, empathy involves offering personalised care and attention. The model has become a common tool in survey-based research, helping organisations compare service quality across time periods or customer groups (Parasuraman et al., 1988).

Despite its popularity, SERVQUAL has drawn criticism. Carman (1990) was among the first to challenge its universal applicability. In his empirical studies across different service sectors, he found that the five dimensions often overlapped or failed to reflect sector-specific nuances. He concluded that the model should not be used as a one-size-fits-all solution but rather adapted to suit each specific context. Morrison Coulthard (2004) took a different approach by reviewing a broad range of studies instead of collecting new data. Her findings echoed Carman's concerns: SERVQUAL often requires modification before it can be applied effectively in practice. Both argue for tailoring the model to the unique characteristics of the industry in question, in order to accurately assess customer perceptions. Further critique has come from Gilmore and McMullan (2009), who focused on the model's methodological limitations. In particular, they questioned its dependence on standardised quantitative scales. While numerical data can highlight general patterns, they argued that it often falls short in capturing the subtle, context-dependent aspects of service experiences. To address this, they recommended supplementing quantitative methods with qualitative techniques such as interviews and focus groups. According to their research, a more balanced and flexible approach that combines both methods offers a fuller and more accurate picture of service quality.

2.2 Technology Acceptance Factors

Technological innovations are not automatically accepted by end users. To understand the conditions under which users are willing to embrace new systems, a theoretical framework is indispensable. The next section therefore discusses the Technology Acceptance Model, complemented by models and subsequent extensions developed specifically to better explain technology acceptance in customer-facing contexts.

2.2.1 The Technology Acceptance Model

In the 1980s, organisations increasingly adopted new information systems, such as word processors and databases. These developments raised important questions about why some employees readily accepted new technologies while others resisted them. In response, Fred Davis (1985, 1989) developed the Technology Acceptance Model (TAM), a framework designed to explain and predict customer acceptance of information technology. TAM posits that acceptance is primarily driven by two key beliefs: perceived usefulness (PU) —the degree to which a person believes that using a particular system would enhance their job performance—and perceived ease of use (PEOU)—the degree to which a person believes that using the system would be free of effort. These beliefs shape the customers' attitude toward using the system, which subsequently influences their behavioural intention to use, ultimately leading to actual system use.

To make the model more applicable in more complex contexts, TAM has been further developed over the years. For instance, TAM2 (Venkatesh & Davis, 2000) added a social component to the model. This means that employees not only rely on their estimation but also consider the expectations of significant others around them, such as colleagues or supervisors. This social influence can reinforce or inhibit willingness to use technology, especially when there are social pressures or normative expectations. TAM3 (Venkatesh & Bala, 2008) built on this and added factors such as computer anxiety, customer experience, and confidence in one's ability to use technology successfully, among others. Eventually, this led to the UTAUT model (Unified Theory of Acceptance and Use of Technology), by Venkatesh et al. (2003). They integrated eight prominent models to further explain technology acceptance, including by bringing in the role of age, gender, and previous experience as moderators.

2.2.2 The shift from organisation to customer perspective

While these models were developed mainly for use within organisations, they are less sufficient when dealing with consumers who use technology voluntarily, for instance in the context of online shopping, mobile apps, or digital services. For this reason, the UTAUT2 model (Venkatesh et al., 2012) was developed. This model introduces three additional factors specific to consumers. First, hedonic motivation plays a role, or the pleasure and satisfaction a person experiences while using technology. Second, price value is added, meaning that consumers continuously weigh up the expected benefits of the technology against the cost or effort involved in using it. Third, habit, or habitual behaviour, matters: technology that has been used successfully and repeatedly before is more likely to be accepted again because it has been integrated into daily routines.

The rise of artificial intelligence (AI) in consumer applications such as chatbots, recommendation systems, and virtual assistants has once again led to the need for new explanatory models. Unlike traditional technologies, AI systems often operate autonomously and make their own decisions based on data, and their operation is not always understandable to customers. In this context, Pramanik and Jana (2025) introduced the AIEPSAM (AI-Enabled Product and Service Acceptance Model) model. This model states that factors such as algorithmic transparency, data privacy, and a feeling of control over the technology play a central role. When customers feel that they understand how the AI system arrives at certain outcomes, and that their personal data is processed safely and ethically, they are more likely to be willing to accept the technology. Lack of transparency or control, on the other hand, can lead to distrust and resistance. Recent research shows that consumers value AI technologies mainly for the immediate benefits they bring. Choi (2023) and Hasija and Esper (2022) emphasise that functional features such as speed, convenience, efficiency, and personalised support play a decisive role in the acceptance process. Customers appreciate when AI systems reduce waiting times, make relevant recommendations, or streamline the service process. These tangible benefits increase perceived usability and satisfaction and can partially offset any concerns about transparency or data usage, for example.

These findings highlight a broader shift within technology adoption models: from purely rational or ethical considerations to a more experience-driven and contextual assessment. In summary, the use of AI requires an approach in which both structural factors (such as control and trust) and direct customer benefits combine to determine willingness to adopt.

2.3 The Hybrid Support Model

The rise of hybrid customer support where AI and human support work together places new demands on how customer satisfaction is achieved. This section defines the hybrid model and discusses what factors influence customer satisfaction, such as personalisation, escalation processes and trust in AI.

2.3.1 The Hybrid Support Model Defined

Before the integration of artificial intelligence, customer support was the domain of human employees. In call centers and service departments, communication by phone and letter was central, and personal interaction required substantial emotional engagement. Taylor and Bain (1999), in their study of Scottish call centers, highlighted how emotional labour (employees managing their emotions to meet service expectations) as first conceptualised by Hochschild (1983), was a defining feature of such work. However, they also underscored the challenges of this model, such as work intensification, restricted autonomy, and the pressure of standardization, which often constrained the quality of interaction despite employees' emotional efforts. Inavolu (2024), states: “implementing hybrid systems that combine AI with human support can help manage routine inquiries while escalating complex or emotionally charged interactions with human agents” (p.19). This creates a hybrid model in which AI and human agents complement each other for an optimal customer experience.

2.3.2 Advantages and Limitations of the Hybrid Model

Academic literature shows that hybrid customer support can contribute to higher customer satisfaction in several ways. First, AI systems such as chatbots and virtual assistants can manage simple and frequently asked questions quickly and consistently, reducing the time customers must wait and helping them faster (Wiethof & Bittner, 2022). This increases the ease of use and accessibility of customer support, directly contributing to a more positive customer experience. Moreover, findings by Uzoka et al. (2024) highlighted findings from existing studies that indicate that AI-driven automation can manage up to 70% of routine customer queries. This significantly reduces the workload for human employees, allowing them to better focus on more complex or sensitive customer interactions. Furthermore, research conducted by Susanto and Khaq (2024) indicates that start-up enterprises with a well-executed AI framework can realise savings of up to 20% in operational costs, while concurrently enhancing efficiency.

The rise of artificial intelligence has significantly changed traditional customer support. AI applications such as chatbots and virtual assistants can now handle many routine tasks efficiently and consistently, reducing customer wait times and improving the overall customer experience (Wiethof & Bittner, 2022). This strategic reallocation allows organisations to optimise the use of their staff and resources, reducing the need for large support teams and associated overheads (Anozie et al., 2024; Patil, 2025; Singh, 2025a). Moreover, AI systems can operate continuously, 24 hours a day, without breaks or rest periods, ensuring constant availability of customer support (Huang & Rust, 2018). An additional advantage is that AI systems can proactively detect potential problems through real-time data and sentiment analysis, allowing organisations to detect and resolve customer problems even before they escalate (Tarra & Mittapelly, 2023). Finally, as discussed by Anozie et al. 2024) these systems are able to analyse large amounts of customer data and make personalised recommendations, which customers often perceive as a form of customization and appreciation, thus contributing to their satisfaction and loyalty.

While AI applications offer significant advantages for routine interactions with customers, there are also obvious limitations. One of the most important is the inability to convey true empathy, a key ingredient for customer satisfaction. Research shows that empathy in service interactions promotes emotional connection, trust, and perceived care, which strongly influence how customers rate the quality of support (Bove, 2019; Liu-Thompkins et al., 2022). In contrast, AI-driven systems such as chatbots and virtual assistants often struggle to interpret and respond to emotional nuances in customer communications. This so-called "empathy gap" becomes especially problematic in situations where customers are angry, frustrated, or emotionally upset. Studies by Huang and Rust (2023) and Markovitch et al. (2024) show that the lack of empathetic responses at such times not only leads to dissatisfaction but can also erode trust, especially when human escalation is slow or unavailable. Thus, while AI is effective in providing immediate responses, the limitations in emotional sensitivity make human empathy an irreplaceable component of effective customer support. Another major concern is the error rates of AI-assisted customer support systems. Despite technological advances, problems remain, such as speech recognition errors, inaccurate solutions, or the inability to handle complex requests properly (Izadi & Forouzanfar, 2024).

Moreover, the adoption of hybrid customer support models requires significant investments, not only in technological solutions such as virtual assistants and chatbots but also in the supporting infrastructure and operational adjustments needed to enable smooth collaboration between AI systems and human employees (Leocádio et al., 2024). The article emphasises that the integration of AI-powered human-robot collaboration requires a careful and ethically sound approach to limit negative impacts on employees and ensure that they can focus on more complex and empathetic tasks that AI cannot take over (Leocádio et al., 2024).

2.3.3 Collaboration Between Humans and AI

The interplay between human and machine intelligence has led to significant advances, particularly in complex contexts where hybrid collaboration is essential (Arslan, 2024; Dellermann et al., 2021). Humans remain vital in the design, training, and refinement of AI systems, while ethical considerations and contextual awareness must be integrated throughout their development and use (Arslan, 2024). At the same time, integrating human and artificial intelligence poses challenges. Aligning diverse disciplines and technologies demands careful system design and continuous evaluation to ensure both sides complement each other effectively (Dellermann et al., 2021). AI must interpret human input accurately, while employees need to trust and engage with AI-generated information (Arslan, 2024; Dellermann et al., 2021).

In practice, AI now supports human agents in real-time during customer interactions. By analysing customer data, preferences, and behaviour, AI can suggest appropriate responses or next steps, enabling faster and more tailored service (Leocádio et al., 2024). Automation of repetitive tasks and relevant recommendations also enhance consistency and efficiency in customer support (Blaurock et al., 2024). Moreover, AI contributes to service quality by offering employees real-time recommendations during conversations, helping them to align their communication with organisational standards and customer expectations (Reinhard et al., 2024). AI also plays a role in the intelligent routing of customer queries. By assessing the complexity of incoming issues, AI systems determine whether a query can be handled by a chatbot or requires human intervention (Jain et al., 2018; Uzoka et al., 2024). In addition, Montgomery and Damian (2017) analysed millions of support tickets and developed a predictive model with nearly 80% accuracy for identifying escalations. Their study illustrates how combining automated tools with human expertise improves both efficiency and problem anticipation. Together, these examples demonstrate how AI is increasingly integrated into customer support, not only before or after human involvement but also during live interactions, forming a collaborative model that strengthens the customer experience.

2.4 Industry context

To fully understand the dynamics of hybrid customer support in this study, it is essential to consider the specific characteristics of the software industry. This sector differs from traditional industries in several keyways, which have implications for both the delivery and perception of customer support. This section discusses three important aspects: the economic and strategic characteristics of the software industry, the evolving role of customer support within software firms, and the differences in customer experience that influence support experiences. Based on this, 3 hypotheses are developed.

2.4.1 Software Industry as Research Context

The software industry is relatively young. Its origins date back to the early 1950s, when it was still common practice to sell software and hardware as a single package. The term software was first used in 1959 (Campbell-Kelly, 1995). Nowadays, the software industry is one of the most dynamic and international sectors in the world, with characteristics that set it apart from traditional industries. The core of this difference lies in the nature of software as a digital good. As Buxmann et al. (2012) highlight, the variable costs of software are almost zero once the first copy is developed. This leads to exceedingly high margins on license revenues, which, according to Cusumano (2004), can be as high as 90-100%. This economic principle explains why software companies focus heavily on selling licenses, while additional services such as implementation and maintenance ensure stability and customer loyalty. Another important theoretical aspect is the concept of network effects. Buxmann et al. (2012) argue that software markets are often characterised by winner-takes-all dynamics. This means that once a software solution reaches a critical mass of customers, it becomes increasingly dominant due to network attractiveness. This is especially visible with platform software, where, for example, API ecosystems and integrations further increase its attractiveness. These network effects are in line with theories by Katz and Shapiro (1985), who argue that the value of a product increases as more customers adopt it.

The software industry is further characterised by flexibility and modularity. The software can easily be offered in different versions and packages, allowing companies to respond to diverse customer needs and market niches (Buxmann et al., 2012). This fits within the literature on mass customization of Pine et al. (1993), which describes how products and services can be tailored to individual customer needs without sacrificing the economies of scale that come with standardization. Buxmann et al. (2012) further describe that software development is often subject to principal-agent problems: developers and customers do not always have the same interests, making incentives and control mechanisms crucial. This applies not only to development but also to services such as implementation and support, where trust and reputation of service providers are central. The international and digital nature of software means that geographical boundaries hardly play a role. Buxmann et al. (2012) points out that software can be developed and delivered anywhere in the world via the Internet, creating intense global competition. This is in line with the theory of 'the flat world' (Friedman, 2005), in which globalization and digitalization create a more level playing field. Finally, standardization plays a major role in the software industry. Buxmann et al. (2012) address standardization issues from a game-theoretic perspective. Companies must balance between standardization (for interoperability and economies of scale) and differentiation (to differentiate themselves). This theoretical framework provides insights into how companies base their strategy in a market where compatibility and lock-in are key success factors. In summary, the literature shows that the software industry is characterised by digital economies of scale, network effects, international competition and the tension between standardization, and differentiation. These theoretical concepts provide a foundation for further research on strategic choices within software companies, such as the deployment of AI, the structure of hybrid customer systems, or the role of platform ecosystems.

2.4.2 The role of customer support in software companies

Within software companies, customer support has traditionally been transactional and reactive, mainly focused on answering questions and solving problems. However, due to the nature of software products, which are regularly updated and depend on continuous feedback, there is a growing need to transform customer support into a proactive and anticipatory role. This represents a shift from passive interaction to an active role in collecting, consolidating, and relaying customer feedback to R&D, partly because software versions have a shorter lifespan due to continuous deployment (Dakkak et al., 2022). Providing support within the enterprise software sector typically requires a higher level of technical expertise than in many other sectors. This is due to the complex nature of enterprise software products, where employees are responsible for analysing and solving problems related to installation, configuration, and integration with other systems. Thus, employees in enterprise software technical support (ESS) must have both technical and communication skills, with technical expertise being particularly valued by returning customers (Ramasubbu et al., 2007).

In the software industry, customer support is much more than just demand handling. According to Bosch et al. (2013), customer support forms a direct feedback loop to product development, allowing software companies to continuously improve and innovate. Employees in this industry combine communication skills with technical expertise to turn customer feedback into concrete areas of improvement for new versions and features. As Blocker et al. (2011) argue, in the ICT sector, companies must account for differences in customers' technical expertise and expectations when shaping their innovation processes and customer support strategies. Since software companies have many similarities with the ICT sector, whereas the complexity of the product is there, the same assumption can tentatively be made for software companies.

2.4.3 Differences in Customer Experience with Product

As already mentioned, the software industry is characterised by complex, rapidly evolving products, and a wide variety of customers. In many cases, the level of knowledge and experience of customers varies widely: some customers are technically savvy and have extensive experience with system configurations, while others have only basic knowledge and focus mainly on simple user questions. This possible leads to fundamentally different needs and expectations within customer support. Customer experience in this context refers to the knowledge and skills customers possess in using a specific product or system. According to Alba and Hutchinson (1987), expertise consists of both declarative product knowledge and procedural skills resulting from repeated interactions. The role of customer characteristics comes into additional focus in hybrid support environments, where AI chatbots and self-service systems handle routine queries. AI is generally perceived as effective for low-complexity tasks, especially by inexperienced customers who benefit from quick and accessible help (Inavolu, 2024; Wiethof & Bittner, 2022; Xu et al., 2020). At the same time, appreciation for AI decreases in more complex incidents that require context, interpretation, and domain-specific understanding: a situation in which especially technically proficient customers end up (Babar et al., 2025; Khan & Mishra, 2023). For this reason, this study formulates the following hypotheses:

H1*: The perceived quality of AI-integrated customer support varies across customer segment, depending on their level of experience with the product.*

Inexperienced customers are more likely to ask simple questions and seek quick, accessible help. Since AI systems are actually strong at handling routine tasks, we expect these customers to rate AI support positively.

H1a*: Customers with less experience, who are relatively more likely to submit simple or knowledge-oriented queries, experience AI support as more helpful and effective.*

Experienced customers, on the other hand, are more likely to deal with complex configurations or context-sensitive incidents. Because AI often falls short in these, they will prefer human support to AI-based help.

H1b*: Customers with more experience, who mainly submit complex or configuration-oriented incidents, perceive AI support as less effective than human support.*

These hypotheses highlight the importance of a differentiated approach to AI integration in customer support, especially in industries like the software industry where both the product and the customer base are above average in complexity. When customer characteristics and incident type are considered in the design of hybrid support models, it can contribute to more effective service delivery and higher customer satisfaction.

3. Methodology

3.1 Research Design

The research methodology chosen follows a qualitative case study approach. Creswell (2013) argues that qualitative research is used to explore in depth how individuals or groups make meaning of social or human issues. The aim is to generate context-specific, rich, and descriptive knowledge, rather than generalizable findings.

Given that both the practical implementation of AI within customer support at AFAS is recent, and that the academic literature on this intersection is limited, a case study is particularly suitable. Yin (2009) defines a case study as "an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between the phenomenon and context are not clearly evident." (p.18). This is especially relevant here, as both the technological developments and their organisational implications are still unfolding. The dual newness, in practice and theory, calls for a rich, explorative data approach, allowing room for unexpected patterns or insights to emerge.

The choice of AFAS as a case study was deliberate: the company operates a uniform hybrid customer support model in which all customers, regardless of question type or expertise, follow the same AI-driven route. Through a chatbot and automatically linked help articles, the system first tries to provide a solution independently; only if this fails, an employee is called in. It is precisely this standardised approach that makes AFAS suitable for investigating how customers with different levels of experience value this support, and to what extent their perceptions differ within a similar structure. A multiple-case study was deliberately avoided, as AI integrations vary greatly from one organisation to another. This would make any differences in customer perceptions more difficult to attribute to customer characteristics rather than contextual variation.

3.2 Data Collection

Two complementary methods were used to gain insights into customer satisfaction within the hybrid support model: (1) analysis of customer feedback logs and (2) semi-structured interviews. This combined approach was provided to identify both broad patterns and deeper causes of (dis)satisfaction, in line with the research question on differences between customer groups. The purpose of analysing the feedback logs was to get an overall impression of AFAS customers' perceptions of the hybrid customer support model. Subsequently, through qualitative research involving interviews with both experienced and inexperienced AFAS customers, the underlying reasons could be discovered.

3.2.1 Feedback Logs

The analysis started with feedback logs collected digitally after customers had completed the AI tools and before contacting an employee. These logs included a numerical satisfaction rating (1–5) and an open-ended comment field in which customers reflected on their experience. These entries offered initial insights into recurring themes, customer frustrations, and sentiments related to the support process. However, it is important to acknowledge that not all customers leave feedback after a support interaction. The feedback logs in this study were voluntarily submitted, which introduces a degree of response bias. According to Van Doorn et al. (2010), customers are most likely to write reviews when they feel strongly involved with a brand or experience. Such customer behaviours, in the article known as Customer Engagement Behaviours, are often stimulated by intense positive or negative emotions. Because moderate experiences generally give less reason to take action, there is a risk that online feedback channels mainly reflect the extremes of the customer experience (Van Doorn et al., 2010). As a result, these logs offer valuable, but not fully representative, insights into the hybrid support experience. To account for this, the interview phase was designed to include customers across a range of satisfaction and experience levels, offering a more balanced view of customer sentiment. At this stage, no explicit segmentation was made based on the experience of the customers. Instead, the aim was to explore general perceptions and patterns, which then served as exploratory input to inform the development of the interview guide. This strategy ensured that interviews could be tailored to themes already observed in practice, increasing their relevance and contextual depth.

3.2.2 Semi-Structured Interviews

After the initial log analysis, 12 in-depth interviews were conducted with AFAS customers. The selection was made with a view to variation in the experience level of the participants so different customer perspectives could be included. Semi-structured interviews were chosen because this method allows for both consistency in questioning and flexibility in probing (Barriball & While, 1994). This method enabled a deeper explanation of the personal experiences of customers, while at the same time allowing for room to respond to themes that spontaneously emerged.

The interviews focused on how customers experienced the hybrid support system, both the AI part and the contact with human employees, and how these interactions influenced their satisfaction. The interview guide was developed based on the research questions and the insights gained from the log analysis. Following the five-stage approach by Kallio et al. (2016) consisting of: identifying the prerequisites for using semi-structured interviews, retrieving and using previous knowledge, formulating the preliminary semi-structured interview guide, pilot testing the guide, and presenting the complete semi-structured interview guide. Conducting the pilot was done with Customer Support Manager of AFAS. All interviews were recorded (with consent) and transcribed.

So, the feedback logs were first analysed to get an overall impression of the sentiment and to identify common themes. Interviews were then conducted to further explore the underlying reasons and differences between the customer groups. This sequence supports methodological triangulation and strengthens the trustworthiness of the findings by aligning behavioural data with subjective experience. Although the research is mainly focused from the customer's perspective, it is also relevant to find out why the choice was made to implement a hybrid customer support model from the perspective from AFAS. After all, this could bring significant benefits such as efficiency for the software company. Therefore, an interview was also conducted with AFAS customer support manager, who was also involved in the AI implementations within customer support (see Appendix 2).

3.3 Sampling Strategy Interviews

Purposive sampling was used to select participants. This is a commonly applied qualitative research technique in which participants are intentionally chosen based on specific characteristics that make them particularly well-suited to provide insight into the phenomenon under investigation (Patton, 1990). This approach ensures data richness and relevance by focusing on those most likely to offer valuable and diverse perspectives. In this study, two customer groups were identified: Experienced customers, who have been AFAS main contact for over five years and have submitted predominantly complex, configuration-related issues (<10% basic questions), and inexperienced customers, who have held this role for under five years and have submitted ≥20% knowledge-based/simple queries. This form of criterion-based sampling ensured the inclusion of participants with relevant and contrasting support experiences. Given the natural overrepresentation of experienced customers within the overall AFAS customer base, purposive sampling was particularly suitable. This approach allowed for a balanced representation of both customer groups, which would have been difficult to achieve through quantitative methods such as surveys. A random sampling strategy would likely have resulted in a skewed sample dominated by experienced customers, limiting the ability to compare perspectives across groups. To enrich the data and improve the breadth of insights, maximum variation sampling was applied in parallel. This approach ensured variation not only in software experience but also in the support situations encountered, ranging from questions easily handled through AI to issues that required escalation to human agents. To ensure both relevance and analytical depth, a combination of criterion-referenced and maximum variation sampling was used (Palinkas et al., 2013).

In addition to the experience of customers, two other dimensions were considered to enhance contextual variation: overall customer satisfaction and customer segment. Of the twelve participants, nine reported generally positive support experiences, while three expressed dissatisfaction. Furthermore, efforts were made to include customers from the full spectrum of the customer base of AFAS: First Class, Culture, Education and Healthcare (CoZ), Business Services, and corporate customers. While these two dimensions are not part of the main analytical comparison, they were acknowledged as a contextual factor that may shape how customers in different industries experience the hybrid support model. However, because of the limited number of participants in this category (3 each), it is too limited to conclude them, and because this is closely related to the criteria of experienced and inexperienced, company type is therefore only noted to support more nuanced interpretations of the findings. The total sample size (N = 12) was guided by both theoretical saturation and practical feasibility. In qualitative research, a fixed number of participants is not required in advance; instead, recruitment typically continues until new data no longer provide substantially new insights. Previous research has shown that saturation often occurs within the first 12 interviews (Guest et al., 2006).

3.4 Data Analysis

The collected qualitative data were analysed using thematic analysis, following the six-phase model proposed by Braun and Clarke (2006). This method is widely adopted in qualitative research due to its flexibility and ability to capture recurring patterns within rich, complex datasets. It is particularly well-suited to exploratory case study designs in which theory emerges from inductively derived insights.

The analysis began with an in-depth familiarisation phase, during which all interview transcripts and feedback logs were read repeatedly to develop a grounded understanding of the material. From this foundation, initial codes were generated in a data-driven manner, with recurring ideas and notable phrases tagged across the dataset. These codes were then organised into preliminary themes that reflected shared meanings, which were continually refined, merged, or discarded as the analysis progressed. Particular attention was paid to clarity, coherence, and internal consistency within each theme. In the final stages, each theme was clearly defined and illustrated with representative quotes to preserve the authenticity of the participants' voices. This layered coding structure was particularly valuable in identifying interpretative differences between experienced and inexperienced customers. It allowed the study not only to capture what participants explicitly said but also to explore how they constructed meaning around their experiences with the hybrid support model. A visual representation of the final coding structure was developed to clarify how raw quotes were systematically transformed into abstract themes, thereby contributing to the overall theoretical understanding of customer satisfaction in the context of AI-enabled service environments. The comprehensive data analysis can be found in Appendices 5 and 6. For the analysis of the interview data, two complementary coding schemes were used, each with its function within the research. The first scheme is based on pre-established assessment criteria that are relevant for the evaluation of the hybrid customer support model of AFAS. These pre-determined dimensions offer a structured way to gain insight into how participants assess the quality of the service.

Parallel to this, a second coding scheme was developed, aimed at comparing experienced and inexperienced customers. This scheme did not use pre-defined categories; instead, an inductive approach was chosen in which spontaneously mentioned elements were coded. The analysis focused on three components: the factors that customers themselves identify as important in customer support, their experience of the current hybrid support model, and their wishes or needs for future support. In all these cases, so-called unprompted responses were used, with the emphasis on undirected, open statements from participants. The combination of a predefined assessment framework and an open thematic approach makes it possible to systematically test the extent to which the support model meets customer expectations on the one hand, and to explore differences between customer groups in terms of content on the other. By specifically addressing these themes during the interviews with participants, it was possible to investigate why certain aspects were experienced as positive or negative, and which expectations, needs, or frustrations underlay this. This method contributed to a substantively coherent and methodologically substantiated analysis, in which patterns from the log data could be deepened with qualitative insights from the interviews.

Before the thematic analysis of the customer feedback logs, a set of analysis categories was developed using a hybrid approach, combining both deductive and inductive elements. Inductive thematic analysis is described by Boyatzis (1998) as a process in which themes emerge directly from the raw data, without predetermined categories. Conversely, deductive thematic analysis applies pre-established theoretical frameworks or categories to interpret the raw data, thereby guiding the identification and organisation of themes (Boyatzis, 1998). Fereday and Muir-Cochrane (2006) extend this with a hybrid approach, combining data-driven codes with theory-driven categories. This approach allows for the application of existing conceptual frameworks on the one hand while allowing for new insights from practice on the other, which contributes to the transparency and credibility of the research process. In this study, the approach of Fereday and Muir-Cochrane (2006) was followed.

Five central customer criteria were used to analyse the experiences of customers with the hybrid support model. Three of these criteria were derived from existing literature in the field of service quality somewhat adjusted. The SERVQUAL model (Parasuraman et al., 1988) formed the starting point for including the speed of resolution (responsiveness), the correctness of the solution offered (assurance), and the perceived feeling of being understood during the contact moment (empathy). These dimensions are representative of both the functional and relational side of service provision. In addition, an initial exploratory analysis of the feedback logs showed that customers regularly experienced inconvenience from the transition between AI support and human follow-up, especially when they had to repeat information or experienced uncertainty about the status of their report. This led to the addition of the smooth transition between AI and humans as a fourth criterion. Finally, the perceived customer effort, in terms of time required, actions, or repetition, also appeared to be a recurring theme in the feedback logs. This observation was also supported by the TAM model (Davis, 1985), which states that the ease of use of technology influences the perception of the system and general satisfaction. By using these five customer-oriented criteria as an analytical framework, it was possible to systematically investigate to what extent the hybrid support model matches the aspects that possible contribute to customer satisfaction. At the same time, the open coding during the first coding round left room for additional themes that fell outside this pre-established framework, but which nevertheless proved to be significant within the context of the research.

To analyse the open-ended customer feedback logs submitted after using the hybrid support system, A hybrid thematic analysis was conducted, combining human coding with generative AI assistance (ChatGPT) for efficiency. These comments included both a numerical satisfaction rating (1–5) and a free-text reflection. To identify recurring patterns efficiently, a tailored prompt was used in ChatGPT’s analysis mode (see Appendix 4). The AI was instructed to extract thematic elements related to customer satisfaction. The article by Turobov et al. (2024) shows that generative AI, such as ChatGPT, can effectively help find recurring themes and cluster similar answers in the early phase of thematic analysis. This application can speed up the analysis process and enable a broader exploration of the data. At the same time, the authors stress that AI should primarily have a supporting role: human interpretation and validation remain essential to avoid biases and misinterpretations. Similarly, Bennis and Mouwafaq (2025) demonstrated that AI models such as ChatGPT can generate accurate and consistent initial codes, provided researchers carefully assess and refine these AI outputs to ensure contextual accuracy and depth of interpretation.

To ensure the reliability of this AI-assisted analysis, a manual validation was conducted by randomly selecting and reviewing a sample of 100 logs. The comparison showed a high degree of consistency between the AI-generated categorizations and the manual coding, which supports the trustworthiness of the automated analysis process. To strengthen validity and substantive coherence, the results from the coding were systematically compared with findings from qualitative interviews. This approach was part of a broader mixed-methods triangulation strategy. This iterative, semi-automated method allowed the study to identify the most important factors behind customer satisfaction within AFAS's hybrid customer support both efficiently and in-depth.

3.5 Research Quality

Quality assurance is essential in qualitative research to ensure the credibility and usefulness of the findings. This study applied Lincoln and Guba's (1985) four classic quality criteria: credibility, transferability, dependability, and confirmability. These align with broader validity concepts also applied in case study research by Yin (2009).

Credibility refers to the confidence in the truth of the findings and the extent to which they authentically represent the participants' lived experiences. It was promoted through several strategies: data triangulation (combining interviews and feedback logs), member checking, and peer debriefing with the customer support manager of AFAS. Methodological triangulation, using two fundamentally different methods (qualitative interviews and structured log analysis), enhances credibility by allowing the researcher to examine convergent and divergent patterns in how customer satisfaction is expressed and measured (Lincoln & Guba, 1985). These strategies help ensure that interpretations are grounded in data and resonate with participants' perspectives.

Transferability refers to the degree to which the findings can be applied to other contexts, as judged by the reader, based on rich, detailed description provided by the researcher (Lincoln & Guba, 1985). To ensure this, a detailed description of the context in which the study was conducted was chosen: a medium-sized Dutch software company (AFAS) using a hybrid customer support model in which both AI chatbots and human employees are deployed. Furthermore, the customer profile was specified in the experience level of participants. Through rich quotes from the semi-structured interviews and systematic thematic analysis, an attempt has been made to provide sufficient context so that readers can assess the extent to which the results are relevant to other organisations implementing similar AI-assisted customer support.

According to Tobin and Begley (2004), dependability refers to the stability and consistency of the research process over time, and the extent to which the process is documented in a way that allows for external audit or replication. As Carcary (2009) outlines, key components such as interview schedules, structured coding strategies (e.g. thematic categorization), and reflexive journaling contribute to a transparent and traceable qualitative research process. These elements form part of a comprehensive audit trail that enhances the study's dependability and methodological rigor.

Confirmability refers to the extent to which findings are shaped by the participants and data rather than researcher bias. This was strengthened through careful documentation, reflective memos, the use of direct citations, and triangulation. These practices increase objectivity and support the neutrality of the findings (Carcary, 2009).

Although the research design aimed for methodological rigor, some limitations should be acknowledged. First, customer feedback data were voluntarily submitted and may therefore overrepresent extreme experiences, either from highly satisfied or dissatisfied customers, which could influence the thematic balance. Second, the selection of interview participants may be subject to self-selection bias, as participation was voluntary and based on availability. Finally, the use of generative AI in the initial coding phase, while efficient, may inadvertently introduce algorithmic bias or overlook nuanced contextual cues. These limitations were mitigated through data triangulation, member checking, and manual validation of all AI-assisted insights.

3.6 Ethical Considerations

Ethical research principles were strictly followed throughout the study. All participants received a clear explanation of the study's purpose and provided informed consent before participation. Interviews were recorded only with explicit permission, and all recordings were stored securely and anonymised during transcription. No personally identifiable information is reported, and the data were handled in accordance with GDPR standards. The researcher is currently an intern at AFAS, which granted access to internal processes and participants. While this position provided valuable context and access, it also required extra attention to potential bias. To mitigate this, the researcher maintained a critical and reflective stance, ensured anonymity of all participants, and relied on peer debriefing and method triangulation to enhance objectivity and transparency.

4. Findings

The following findings address how different customer segments perceive the hybrid customer support model. First, the findings of the logs are presented, followed by the findings of the semi-structured interviews.

4.1 Feedback log analysis

Table 1 presents a thematic overview of customer experiences specifically related to the AI tools used in the support process. Of the 769 collected feedback entries, 328 were identified as directly referencing the functioning, usefulness, or limitations of the AI tools. Responses that focused primarily on the content of the underlying software issue, rather than on the AI based assistance, were excluded through a ChatGPT assisted filtering process to ensure thematic relevance. It is important to note that the feedback analysed here was collected before escalation to a human support agent, and therefore reflects only the initial AI driven stage of the hybrid support process. The analysis examined five themes, paying attention to how often each theme occurred, the tone of the responses (positive or negative), and illustrative quotes. The table below provides an overview of the log analysis results for each criterion.

Criteria	Count	Ratio positive negative	Representative quote
Speed of resolution	84	80% negative	**Positive**: "Glad the suggested help articles already answered my question" **Negative**: "In the old days when you could just call, incidents were handled much faster"
Correctness of solution	42	69% negative	**Positive**: "In some cases, the chatbot already gives me the right answer" **Negative**: "I usually just get these basic articles that do not address my problem at all"
Feeling understood	19	100% negative	**Positive**: - **Negative**: "No matter how I phrased it, the AI just didn't get it"
Customer effort	165	80% negative	**Positive**: "Very occasionally it saves effort that a chatbot already answers your problem" **Negative**: "It takes so much more effort to just speak to an employee and many steps are unnecessary"
Seamless transition	18	61% positive	**Positive**: "Nice that you don't have to repeat your story over the phone again" **Negative**: "The handover felt a bit clunky, but it worked out in the end"

Table 1 Results feedback logs divided in themes

The logs clearly show that customer sentiment is predominantly negative. However, it is difficult to pinpoint an exact percentage of negative and positive feedback for all customers of AFAS. This is partly because the feedback logs represent a self-selected sample that is likely to contain more extreme experiences and is not fully representative of the wider customer base. Most feedback responses focused on customer effort, highlighting how AI tools often increased rather than reduced customer effort. In addition, many logs mentioned problems with speed of resolution and accuracy of AI-generated solutions. These themes highlight key pain points in the AI-supported phase of the hybrid model.

4.2 Interview findings

The table below (Table 2) summarises how experienced and inexperienced customers rate the hybrid customer support model on the five key factors of customer satisfaction: speed of resolution, correctness of solution, feeling understood, customer effort, and the transition between AI and human support. For each theme, the dominant experiences of each group are summarised, supported by representative quotes from the interviews. A "+" indicates a positive sentiment, a "=" a neutral sentiment, and a "-"a negative sentiment. In Appendix 5 the extensive results of each participant divided into the 5 themes are presented.

Theme/customers	**Experienced customers**	**Quotes**	**Inexperienced customers**	**Quotes**
Speed of resolution	- Slower, especially for complex issues	"The current speed of response is resolved slower than with the traditional method." (R5)	= Fast for basic queries, more tolerant	"If I ask a basic question… it saves a lot of time." (R8, R9)
Correctness of solution	= Generally accurate for simple problems, not for complex ones	"In 90% of the cases I can find my answer in articles when they are simple" (R3)	+ Help articles often useful, but human expertise remains needed sometimes	"Useful links for simple questions" (R9)
Feeling understood	- Expect more empathy and contextual sensitivity	"Sometimes I feel like the AI-tools don't look at what I actually wrote (R4)	- Notice lack of warmth, appreciate empathy from humans	"The chatbot does not yet work so well that it can replace all human work and empathise." (R12)
Customer effort	- Many steps required, feels like a barrier	"Too many steps before contact with employee" (R1, R2,R3,R4,R5,R6)	± More manageable, but structure still too rigid	"You have to go through many more steps… but I personally find this manageable" (R10)
Seamless transition	+ Appreciate that handover is well-informed and efficient	"Employees are already informed." (R1, R3, R4, R5)	+ Appreciate that handover is well-informed and efficient	"In most cases quite smooth. My previous steps usually automatically forwarded to employee." (R9)

Table 2 Comparison customer satisfaction experienced and inexperienced customers by theme

The comparison across the five themes provides insight into how differently experienced and inexperienced customers perceive the hybrid support process. These differences are most pronounced for speed of resolution, correctness of solution, and customer effort. Regarding the speed of resolution, it is notable that experienced customers often perceive it as insufficient. Experienced customers especially noted that for complex or urgent questions, the AI phase delays access to a human agent. Going through several steps takes time and energy, while they want to be helped quickly and specifically. Inexperienced customers are milder in this. They especially appreciate it when the AI answers simple questions quickly and then experiences the process as time-saving.

On the topic of correctness of the solution, it appears that both groups find the AI-generated articles useful for simple problems. Yet experienced customers indicate that this information falls short as soon as more nuance or specialist knowledge is needed. Inexperienced customers partly recognise this, but more often accept it as long as standard questions are involved. When looking at the feeling of being understood, it is noticeable that experienced customers have higher expectations of empathy and context sensitivity. They feel that the AI sometimes does not interpret their question sufficiently well. Inexperienced customers also notice a certain detachment but find this less disturbing as long as their question is answered functionally. However, both groups miss empathy to some extent in the AI interaction, especially if questions are misinterpreted. The customer effort theme shows that experienced customers perceive the number of steps toward an employee as prohibitive. They feel that the process could be more efficient, especially when their question will not be solved by AI. Inexperienced customers sometimes find the process a bit rigid, but generally more manageable, as long as they feel they are making progress. Finally, one of the most positively rated aspects is the seamless transfer from AI to an employee. Both experienced and inexperienced customers indicate that they like the fact that employees are already well-informed when contact is established. By not having to explain their question again, they experience the support process as efficient and professional. This reinforces confidence in the service. The above insights show that customers' attitude by theme is correlated with the experience level of customers. The next part zooms in further on how these differences are reflected in customer expectations, current experience and future desires.

The tables below (Table 3 and Table 4) show how customers perceive the hybrid support model, focusing on three aspects: what they consider important, how they perceive the current model, and their wishes for the future. This representation is also based on common patterns in the interviews and clearly shows how these three points emerge by customer segment (experienced and inexperienced customers). Whereas Table 2 provides insight into how customers value different aspects of the support model, the tables below provide a structured overview of their expectations, experiences, and wishes. This approach makes it possible to identify friction moments and structural needs more precisely. Appendix 6 provides a detailed overview of the expectations, experiences, and future wishes of both groups.

Expectation	**Experience**	**Future wishes**
Speed and direct access to support agents for complex issues (R1, R3, R4, R5, R6)	The AI process was experienced as cumbersome; too many steps before reaching a human (R1, R2, R4, R5, R6)	Give people with expertise a faster route (R2, R3, R6)
In-depth expertise and personal attention (R2, R4, R6)	AI failed to understand context and lacked depth (R3)	Direct contact with a human agent for complex or urgent cases (R4, R5)
	Fine that you can solve some questions independently (R10, R11, R12)	Recognizing complex incidents and give faster route (R1)

Table 3 Expectations, experiences, and future wishes experienced customers

Expectation	**Experience**	**Future wishes**
Empathy, clear explanations, and reassurance during support (R8, R10, R11, R12)	Fine that you can solve some questions independently (R10, R11, R12)	Personal contact remains crucial when dealing with complex issues (R8, R10, R12)
Human staff easily accessible during support (R7)	AI sometimes hinders access to human contact (R7, R8)	Give customers a choice how they want to get contact (R7, R9, R11)
The speed of resolution (R9)	Sometimes unprofessional when AI doesn't work (R9)	

Table 4 Expectations, experiences, and future wishes inexperienced customers

Tables 3 and 4 offer a deeper insight into how experienced and inexperienced customers differ in their expectations of the hybrid support model, their actual experiences, and their wishes for the future.

For experienced customers, speed and immediate access to a knowledgeable employee are key, especially for complex or urgent questions. This group often experiences the AI part as cumbersome, partly due to the large number of steps required before contact with an employee is possible (R1, R2, R4, R5, R6). The depth of content of AI is also perceived as limited, which means people do not always feel well understood. While some experienced customers appreciate that simple questions can be solved independently, they value recognition of complex situations. Their wish is for the system to refer them to a human expert more quickly when the situation calls for it. Inexperienced customers have other priorities. Above all, they expect clear explanations, reassurance, and control over the process. They like to solve simple questions independently and experience a sense of independence in doing so (R10, R11, R12). At the same time, they find it important that human contact always remains available when the question becomes complex, or they feel uncertain. Some participants indicate that AI sometimes hinders contact with staff (R7, R8), or that handling feels unprofessional when the technology does not work properly (R9). Their main desire is therefore flexibility: being able to choose for themselves when and how they want to make personal contact.

These findings reveal that customers differ not only in how they experience the current system but also in what they consider important for the future. Whereas experienced customers mainly demand efficiency and expertise, inexperienced customers seek trust, freedom of choice, and a sense of control. These differences underline the importance of customization within hybrid customer support.

5. Conclusion, discussion, limitations, and recommendations

5.1 Conclusion

A key driver for integrating AI into customer support is the pursuit of greater operational efficiency. By automating routine interactions and reducing human workload, organisations can provide faster support while optimizing internal resources. However, this should not come at the expense of customer satisfaction.

The research question asked to what extent the hybrid model aligns with key satisfaction factors for different customer groups. This research indicates that a hybrid customer support model, using both AI tools and human support, can offer clear benefits, but that its effectiveness is highly dependent on the level of customer experience. Within the software industry, this factor is particularly relevant: software products are often complex, have frequent updates, and place high demands on customers. Moreover, software companies serve a broad and diverse customer base, in which there are large differences in product knowledge.

Inexperienced customers, with the data showing that there are more likely to ask simple user questions, appear to be predominantly positive about the hybrid model. They appreciate the structured format, the immediate availability of information, and the fact that they can arrive at solutions independently. For this group, the system lowers the threshold for seeking help and provides overview and clarity. For more experienced customers, the situation is different. They usually submit more complex and context-dependent questions, for example around configuration or integration. For them, the AI-driven route provides little added value. The perceived customer effort also plays an important role in this: the compulsory completion of several AI steps before contacting an employee is often perceived by this group as cumbersome and frustrating, especially when the system does not understand the question properly or does not offer an appropriate solution. Moreover, they compare the current system to the previous, more personalised forms of support and more often express disappointment at the lack of depth and relevance in the AI solutions offered. However, this distinction also reflects the different types of value AI offers to customers. For inexperienced customers, the benefits are direct and operational, like speed, clarity, and access to basic information. For experienced customers, the value of AI is more indirect. Although it cannot answer their complex queries, it can support the process by helping to clarify questions, gather context, or route the issue more effectively to human support.

In summary, the hybrid model partially meets what customers care about. Especially in terms of speed and accessibility for simple questions, the model shows itself to be effective. In contrast, the hybrid model still falls short on more complex issues, where expertise, speed, and contextual understanding are crucial. The answer to the research question is therefore nuanced: the hybrid model contributes to customer satisfaction, but only to the extent that the design considers the customers' level of experience, and thus implicitly the complexity of the question.

5.2 Discussion

5.2.1 Explanations for Differences in Customer Perception

There is a clear difference in how experienced and inexperienced customers perceive the hybrid support model. Although both groups use the same uniform system, their expectations and satisfaction levels differ significantly. There are three explanations for this difference.

First, the nature of the questions they tend to ask experienced customers are more likely to deal with complex, configuration-related issues that require contextual understanding. Previous research suggests that such questions are less suitable for AI tools, which perform better with simpler, standardised questions. Inexperienced customers more often ask this kind of question.

Second, the data also suggests that the negative perception among experienced customers is not solely caused by the AI system itself, but by a form of resistance to change. These customers have prior experience with older, more personal support methods and may judge the new hybrid model more harshly due to comparison bias. Conversely, inexperienced customers may lack these prior reference points and thus perceive the current model more positively, not necessarily because it functions better, but because their expectations are more modest.

Third, differences in customers' organisational roles may affect their needs and expectations. At AFAS, experienced customers are often consultants or part of management teams, who are under time pressure and have high expectations of fast, accurate support. Inexperienced customers are often operational staff focused on day-to-day usability. These different goals may influence how they evaluate the effectiveness of the support system.

Although these three factors likely interact, it remains unclear which has the strongest influence on customer satisfaction.

5.2.2 Theoretical Reflection

A striking finding is that negative experiences with the AI tools do not necessarily lead to general dissatisfaction. In several cases, participants indicated that an employee who subsequently handled the situation well managed to restore confidence. This points to the importance of service recovery within hybrid models: the human safety net can partially compensate for failing AI interactions, provided the transition to human assistance is smooth and empathetic. The research findings align with existing theoretical models such as the Technology Acceptance Model (TAM) and the SERVQUAL model. According to TAM, ease of use and perceived usefulness influence technology acceptance. Customers appreciate quick and clear AI interactions for simple queries, but experience frustration when the AI is slow, unclear, or incorrect. The SERVQUAL model emphasises dimensions such as reliability and empathy. AI scores well on consistency and availability but falls short in conveying empathy and context understanding, particularly important aspects in complex or sensitive customer queries. This highlights the importance of human support in complementing AI, especially in situations where personal attention is required.

Moreover, this research shows that a generic hybrid system design is not optimal. Customer groups' preferences and needs vary, which argues for a personalised approach within the customer journey. ‘One size fits all’ turns out to be a sub-optimal strategy in practice. However, it is important to note that the hybrid support system at AFAS is still relatively new. The AI components continue to improve over time, as the system is trained both by processing an increasing number of customer interactions and by incorporating feedback and corrections from support staff. This ongoing learning process is likely to reduce errors and enhance the system’s ability to match customer queries with relevant responses. As the AI better adapts to recurring patterns and phrasing, customers may experience less frustration in the future. Therefore, some of the dissatisfaction reported in this study may be temporary and related to the current maturity level of the system.

5.2.3 Organisational implications

The introduction of AI in customer support not only affects customers, but also employees, and the organisation. These implications vary by function level and require broader organisational rethinking.

For support staff, the shift to AI support means that routine, simple tasks are increasingly disappearing. This changes the required skills profile. Besides technical knowledge, analytical thinking skills, problem-solving abilities and empathy will become more important. The set-up of the support department will also change: smaller first-line teams, more specialised support in the second line, and more emphasis on continuous training. Employees are also needed to monitor the developments of AI by continuing to monitor data critically to keep improving current AI systems. At the organisational level, deploying AI leads to more efficient processes. As shown at AFAS, this can even create room for structural changes such as a four-day working week. In addition, the lower pressure on support staff can give room for supporting a broader product portfolio. In theory, this would allow companies to offer more custom software or even lower prices for support-intensive products, as AI absorbs some of the workload. The related strategic choices do require an integral alignment between IT, HR, and operations.

Finally, the results offer starting points for other sectors. In sectors with less complex customer demands, such as e-commerce or standard banking, the negative effects of AI may not be as pronounced. On the contrary, in domains with high trust or expertise requirements, such as healthcare or legal services, the tensions may be greater. This underlines the importance of sector-specific design and testing of hybrid customer models.

5.3 Limitations

Although this study was carefully conducted, there are certain limitations. The feedback logs were completed voluntarily, so there may be response bias: extreme experiences (both positive and negative) are more likely to be represented. Also, the interviews may contain selection bias because participation was voluntary. In addition, log analysis used AI to identify patterns in customer feedback. This accelerated the analysis process and provided overview but also carries the risk that certain contextual nuances, such as the tone or intention of a comment, may not be picked up as well. To mitigate this risk, additional steps were taken, including triangulation of methods (such as interviews and feedback logs), member checking, and manual checking of AI results. Nevertheless, some caution is needed when drawing conclusions or generalizing the findings to other sectors or situations.

Also, the study population was limited and qualitative in nature (interviews with AFAS customers), making conclusions indicative and not allowing for statistical generalization. Follow-up research is recommended to see to what extent the same insights apply in other contexts, for example, at other software companies or industries, or in. Moreover, it is important to mention that while the uniform structure of the hybrid support system at AFAS, in which every customer goes through the same steps, allows for clear analysis, it also limits generalisability. In more complex organisations, where multiple support channels exist or customer journeys are less standard, different patterns may occur. Future research should therefore also focus on such contexts to test whether the differences found between customer groups hold up there as well.

In addition, the study focuses primarily on customers and leaves out the internal perspectives of employees (such as AI trainers or support staff). Understanding these internal processes could have provided additional explanations of how the hybrid model functions and is perceived.

5.4 Recommendations

Based on the research findings, the effectiveness of the hybrid customer support model strongly depends on how well the system is tailored to the diversity of customer inquiries and user profiles. To strengthen the balance between technological efficiency and customer orientation, five targeted recommendations are formulated below. These aim to enhance customer satisfaction, optimise the use of AI, and reinforce the human component within the hybrid model.

1. Design the support process based on task complexity and customer profile

Avoid a one-size-fits-all approach. Structure the hybrid model so that complex, context-sensitive issues are routed more quickly to human support, either automatically or through human triage. Use customer characteristics such as experience level, usage patterns, or industry, and consider implementing predictive recognition based on historical interactions.

2. Offer choice and preserve customer autonomy

Where possible, allow customers to choose between AI assistance and direct support from an employee. This increases the sense of control and prevents frustration, especially among experienced users. Enable customers to store their preferences so that future interactions can be handled more efficiently and personally.

3. Use AI as a supportive tool, not as a gatekeeper

Limit the use of AI to situations where it clearly adds value, such as in handling routine or frequently asked questions. Avoid positioning AI as a mandatory filter; instead, use it to structure inquiries, gather relevant context, and support staff in their decision-making.

4. Invest in human empathy and service recovery skills

Train support staff explicitly in recognizing dissatisfaction and restoring trust after less successful AI interactions. In hybrid models, it is often the human element that ultimately determines customer satisfaction in more complex or sensitive situations.

5. Develop AI in co-creation with users and support staff

Continuously improve the AI system using feedback from both customer interactions and internal expertise. Combine log data with qualitative insights to increase the relevance and accuracy of AI responses. Also consider implementing reverse triage, where staff can decide to redirect certain requests back to AI if this proves more efficient.

Based on the findings, it appears that the hybrid model needs further refinement in several ways.

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Appendices

Appendix 1: Disclosure of the use of AI tools

By submitting this thesis, I confirm that I have read and understood the university's guidelines concerning the responsible use of AI tools in academic work and fully agree to adhere to them. Between February and 12 June 2025, I used artificial intelligence tools in a responsible and supportive manner. These tools were used to improve clarity of writing, inspire structural decisions, assist with the initial organisation of qualitative data, and occasionally help generate creative ideas. All academic interpretations, critical analyses and final writing were carried out independently.

In the early writing phase, between 10 and 28 February 2025, I consulted ChatGPT-4 (OpenAI Pro) to explore potential structures for the literature review. By entering prompts such as "What is a logical structure for discussing TAM, UTAUT, and AI adoption models in a thesis?", I received suggestions on how to organise the chapter in a coherent way. These insights helped shape the structure of Chapter 2, where the literature transitions from general models to consumer-oriented adaptations and finally to AI-related frameworks. Between 5 and 25 March 2025, I used ChatGPT to refine theoretical definitions and to rephrase certain complex explanations in clearer academic language. For instance, I explored different ways to explain concepts like customer expertise or perceived usefulness, and used AI-generated suggestions as a starting point to formulate my own version.

Between 1 and 12 April 2025, I used the Advanced Data Analysis feature in ChatGPT to explore themes in qualitative feedback data. I uploaded an Excel file with over 100 anonymised customer responses from feedback logs and asked the system to identify recurring sentiments. A prompt used in this process was: "Can you cluster these feedback entries into meaningful themes based on sentiment and topic?" The results offered initial insights into possible thematic categories such as perceived impersonality or efficiency, which were later manually reviewed and coded. I also used ChatGPT for creative input in specific moments of the thesis process. One example is when developing strategic recommendations for different stakeholder levels in Section 5.3. Prompts such as "What kind of recommendations could be relevant at the customer, staff, and organisational level based on AI support systems?" helped me identify new angles. Similarly, when formulating hypotheses, I explored ideas by asking “What theoretical argument supports the expectation that expert users may respond more critically to AI-based support?” These conversations contributed to a more complete reasoning behind H1, H1a and H1b.

From March to early May 2025, I used the ScholarAI plugin to search for peer-reviewed academic literature on topics such as empathy in AI, customer support satisfaction, and consumer knowledge heterogeneity. I also used the tool to verify APA 7 citations and ensure that all sources included a correct DOI. Finally, during the final phase from 5 to 12 June 2025, I used the free version of Grammarly to review grammar, sentence structure and academic tone in the abstract, discussion, and conclusion. All suggestions were applied manually after individual assessment.

AI tools were never used to generate full paragraphs or interpret data without critical human review. Their use was limited to support tasks and exploratory idea generation. The final thesis reflects my independent academic work.

Appendix 2: Transcription interview manager customer support Sven de Zeeuw

Koen: Zou je wat kunnen vertellen over hoe de wekwijze van de customer support van AFAS over de afgelopen 5 jaar is veranderd?

Sven: Ja 5 jaar is best wel een lange tijd. Ik werk bijna 4 jaar op de afdeling support. Er zijn best wat dingen veranderd, ook wat teamveranderingen doorgemaakt. Dus er zijn 4 supportteams die allemaal ingedeeld zijn op branche. Dat hebben we twee jaar geleden veranderd naar 3 teams. Dus daar zijn wat dingetjes veranderd. Maar qua werkwijze is er ook wel het een en ander veranderd. Tegenwoordig worden bijvoorbeeld alle incidenten op naam gezet. Dus als incidenten worden ingestuurd worden die automatisch op iemands naam gezet. Dus er moet niets meer zelf te worden opgepakt door de mensen op Support zelf. Ooit hebben we het doel dat op het moment dat als je als klant een incident instuurt, dat dan meteen de naam van degene die het gaat behandelen erbij staat. Dus als jij als klant Koen een incident instuurt staat er bijvoorbeeld. Bedankt voor uw incident, Sven gaat er direct mee aan de slag. Andere grote verandering is onder andere het insturen van een incident. Daar gebruiken we sinds 1 januari van dit jaar de instuurhulp voor. We hebben heel veel helpdocumentatie, dus heel veel artikelen die specifiek gaan over bepaalde onderwerpen, waar klanten dus getraind worden om ook zelfstandig dingen oplossen. In hoeverre wil je eigenlijk dat ik dit uitleg?

Koen: Nee dat is prima. Ik grijp wel in anders hoor

Sven: ah oke. We hebben veel help documentatie beschikbar en als support maken wij wel echt onderscheidt in de kennisvragen bij klanten en dingen die echt fout gaan in de software. En bij de kennisvragen zorgen wij er echt voor dat het beschreven staat in de help. Maar nog steeds zien we dat ongeveer, nou tot januari, 50% van de vragen die werden ingestuurd alsnog kennisvragen waren, ondanks dat we dit al beschreven hadden in de help. En daar willen we gewoon van af. Dat is gewoon veel werk wat we niet zouden hoeven doen als onze klanten in principe goed zoeken in de help. Want dat is gewoon allemaal openbaar beschikbaar. We hebben dus heel veel initiatieven om dit tegen te gaan eigenlijk. Als iemand veel kennisvragen instuurt dan bellen we proactief een keertje met de vraag: hoe kunnen we ervoor zorgen dat jij eerst in de help goed gaat zoeken en ook tips geven om met de juiste zoektermen te komen.

Maar een stap die we extra hebben gedaan is dat op het moment dat een incident wordt ingestuurd, een AI-model gaat kijk vak welke vraag wordt eigenlijk gesteld en welke helpartikelen sluiten het beste aan op deze vraag. Dus daar kunnen ze mogelijk het antwoord in terugvinden. En dan nog een ander ding: De AI stelt momenteel ook vervolgvragen en aanvullende vragen. Dus als je bijvoorbeeld stuurt dat je niet kan inloggen, dan wordt de vraag gesteld: kan je niet inloggen op Profit, Insite of in Pocket. Het stelt dus eerst een aantal duidelijke vragen. Dus ook dat gebeurt door dat AI model. Dus eigenlijk wat de klant instuurt, een bepaalde vraag en dat kan zowel een kennisvraag zijn als een daadwerkelijk softwareprobleem wordt door een AI-model gehaald. Hierop volgen AI gestuurde relevante artikelen die aansluiten op het probleem dat ze vrij kunnen definieren. Daarnaast worden er nog aanvullende vragen gesteld zodat het probleem voor ons duidelijker wordt bij de supportafdeling. Pas na deze stappen komt hij terecht op onze supportafdeling.

Koen: Duidelijk. En klopt het ook dat jullie voorheen makkelijker telefonisch bereikbaar waren en dat dit door de jaren heen zo is veranderd dat klanten eerst een AI-route moeten doorlopen voordat ze in contact kunnen komen met een medewerker?

Sven: Ja dat klopt. Tot 1 juli vorig jaar konden klanten, op het moment dat je een contactpersoon was en dat betekent dat je in ons CRM-systeem gekoppeld staat met het telefoonnummer, gewoon telefonisch met ons contact opnemen. Dus als je dan belde kwam je meestal terecht in de wachtrij en als wij de telefoon dan opnamen gingen we je direct verder helpen.

Koen: Ja en waarom hebben jullie destijds besloten om hiervan af te stappen?

Sven: Ja we merkten dat veel klanten dat makkelijk gebruikten. Eigenlijk werden heel veel gebruikersvragen gesteld via deze weg. Dus als iemand bijvoorbeeld op een administratieve functie er niet uitkwam zij het heel makkelijk vonden om het telefoonnummer te bellen ook omdat je dan altijd wel gewoon netjes antwoord kregen. Maar we wilden echt dat de klanten wat zelfstandiger zouden worden omdat er ook heel veel antwoorden op die kennis en gebruikersvragen op onze klant. afas website te vinden was maar veel klanten deze moeite simpelweg gewoon niet wilde nemen. Klanten hebben nog steeds de optie om direct te bellen dus het is niet zo dat we de telefoonlijn helemaal dicht hebben gegooid maar dan moet het wel echt een spoedvraag zijn en het belang dat het softwareprobleem direct opgelost wordt belangrijker zijn voor het functioneren van het bedrijf.

Koen: En op het moment dat jullie afstapten van deze traditionele methode van bellen. Welk gevoel hadden jullie wat hiervan de invloed was op de klanttevredenheid?

Sven: Ja we nemen in het oog van de klant wel wat weg op deze manier. Zeker in het begin waren er best wel een aantal klanten die gewend waren om gewoon makkelijk de telefoon te pakken. Dus wat betreft vond een deel van onze klanten het lastig. Maar er waren ook wel klanten die er blij mee waren. En nu pakken we incidenten op, op basis van wanneer het incident is ingestuurd. Dus op het moment dat een klant alle informatie netjes in een incident zet en instuurt en dan op zijn beurt wacht is hij sneller aan de beurt omdat er geen klanten tussendoor komen die belletjes plegen om iets wat ze eigenlijk dus zelf hadden kunnen vinden. Dus we merken dat de doorlooptijd in ieder geval eerlijker is.

Koen: Merken jullie dit alleen in de doorlooptijd of merken jullie ook dat er op deze manier minder medewerkers beschikbaar hoeven te zijn?

Sven: Nee dat niet per se. Het aantal medewerkers in die tijd was dan ook ongeveer hetzelfde dus in dat opzichte zijn we er niet op achteruit gegaan.

Koen: En het aantal incidente dat er nu op een dag worden opgepakt? Merken jullie hier wel echt een verandering in?

Sven: Ja nou dat niet per se maar het aantal incidenten dat wordt ingestuurd door klanten is wel echt omlaaggegaan. Hieruit zou je dus kunnen concluderen dat klanten meer dingen zelf uitzoeken en hier daadwerkelijk ook uitkomen.

Koen: Ja, je hebt het net eigenlijk al wel benoemd maar wat was het voornaamste wat jullie wilden bereiken met de vernieuwde instuurhulp die jullie begin 2025 hebben doorgevoerd.

Sven: Het verminderen van het aantal kennisvragen bij ons op de afdeling. Maar ik benader het nu een beetje vanuit ons alleen is de klant ook sneller geholpen als ze zelf de juiste informatie ter beschikking krijgen of de juiste informatie weten te vinden in plaats van dat ze een incident moeten insturen en moeten wachten voordat iemand contact opneemt. Dus als ze iets vinden via de help hebben ze de informatie direct paraat voor de neus. Dus aan de ene kant is het aantal kennisvragen bij ons verminderd maar ook het helpen van klanten aan het sneller helpen van een antwoord.

Koen: En hoe is deze manier ontvangen bij de klant?

Sven: Ja wisselend. Er is dus een gedeelte blij mee omdat ze aangaven dat ze eerder moeite hadden om uit de voeten te komen met de help en als ik nu een incident instuur krijg ik helpartikelen door middel van AI waar ik vaak mijn antwoord in kan vinden. Tegelijkertijd hebben we ook mensen die al heel veel uit zichzelf gebruik maakte van de help voordat ze contact met ons opnamen en wel al in staat waren die informatie te vinden. En voor die klanten kan het soms een beetje dubbel voelen dat zij gehinderd worden om contact met ons te krijgen.

Koen: En waarom is er destijds besloten om voor iedereen, ongeacht het type klant, dezelfde route te laten doorlopen.

Sven: Omdat we ergens moesten beginnen. Dus we wilden het dan ook niet te complex maken in het begin. Dat is ook wel meestal hoe we bij AFAS iets aanpakken. We gaan iets doen en dan gaan we kijken wat de ervaring hiervan is en op basis daarvan gaan we het verbeteren. Ons voornaamste doel was om het aantal kennisvragen die terechtkomen op de afdeling te verminderen. Dit scheelt voor onze werknemers gewoon heel veel tijd die je overhoudt voor de complexe vraagstukken. Het aantal kennisvragen lag voor deze implementatie namelijk rond de 50% en naar schatting nu rond de 10% dus dat is wel echt een ontzettend groot verschil. Het risico wat wij hierbij wel hebben gelopen is dat klanten onze service misschien lager zal beoordelen. Althans, een deel van de klanten. Maar wij hadden ook wel het idee dat klanten aan deze methode gedurende de tijd wel konden gaan wennen ondanks dat de verwachting was dat in het begin er wel geklaag zou komen vanuit een deel van de klanten. Het doel is ook om deze AI-integraties steeds verder te optimaliseren en deze zo te trainen dat het wel echt accuraat is. Dit is namelijk een proces dat verbeterd over de tijd en om dit op de juiste manier te trainen hebben wij ook echt onze collega's van de afdeling nodig. En de software-industrie blijft gewoon ingewikkeld. Als er daadwerkelijk softwareproblemen optreden bij klanten willen zij gewoon zo snel mogelijk geholpen worden en dit soort vragen zien wij in de toekomst ook nog niet snel opgelost worden met alleen AI. Dat is ook echt niet ons doel. Wij willen het gewoon als hulpmiddel blijven inzetten.

Koen: En hebben jullie destijds ook doelstellingen gemaakt?

Sven: Nee eigenlijk niet, ja het aantal kennisvragen verlagen en dat gaat zeker de goede weg op maar niet per se percentages of dat soort dingen.

Koen: Maar hebben jullie vooraf wel concreet besproken wat de gevolgen van dit kunnen zijn op de klanttevredenheid?

Sven: Goede vraag. Dit hebben we eigenlijk niet gedaan. Dit komt omdat we het meer vanuit support hebben benaderd dan vanuit de klant zelf. Zonder de klant helemaal uit het oog te verliezen want het doel is wel dat het uiteindelijk ten goede komt van de klant omdat we de vragen die wel bij ons binnenkomen sneller kunnen oplossen. Dus als je het zo bekijkt is iedereen erbij gebaat.

Koen: En hoe ziet u de toekomstige rol van AI in de customer support. Worden er nog nieuwe toepassingen overwogen?

Sven: Overwogen zeker. We hebben een complex product. We zijn er wel actief mee bezig om verder te implementeren. Maar nu vooralsnog gewoon op onze eigen afdeling. Veel grotere organisaties zijn best wel afhankelijk van onze producten. Daarom zullen we onze eigen support ook niet snel loslaten of overlaten aan AI. Maar we zien dus wel allemaal toepassingen om ook onze medewerkers te trainen en om dit soort dingen makkelijker te maken. Dus we kunnen er wel voor zorgen dat we minder vragen krijgen maar toch tevredener klanten kunnen krijgen. Dus dat we minder snel ingeschakeld worden en als we wel worden ingeschakeld sneller kunnen handelen.

Appendix 3: Interview guide qualitative research

Doel en achtergrond (voor deelnemers)

Ik ben op dit moment bezig met mijn afstudeerscriptie en onderzoek in welke mate de integratie van AI in customer support bijdraagt aan klanttevredenheid, en of dit verschilt per klantgroep. Het doel van dit onderzoek is om te begrijpen welke aspecten klanten van softwarebedrijven het belangrijkst vinden in klantondersteuning, en in hoeverre deze voorkeuren aansluiten bij de manier waarop AFAS haar hybride supportmodel inzet.
Dit model combineert AI-technologie (zoals chatbots en automatisch voorgestelde help-artikelen) met menselijke ondersteuning. Daarbij wordt gekeken of de behoeften van klanten verschillen afhankelijk van het type vraag dat zij stellen – bijvoorbeeld een eenvoudige vraag over een functie, of een complexe vraag die meerdere stappen of diepgaande uitleg vereist.

1. Start van het gesprek – Algemene ervaringen
- Wat doet u meestal als eerste wanneer u een probleem ervaart met de software,
voordat u een incident indient? (vraagt u om hulp bij collega's, zoekt u in helpartikelen)
- Hoe vaak stuurt u over het algemeen een incident in?

2. Ervaring met de instuurhulp (AI-stap)
- Wat vindt u het meest belangrijk in customer support van een softwarebedrijf? En verschilt dat bij eenvoudige of juist complexe vragen? (1. Expectation)
- Hoe ervaart u de eerste stap van het supportproces, waarbij u via de instuurhulp uw probleem beschrijft en AI automatisch artikelen of vervolgvragen voorstelt? Leest u deze suggesties meestal, en vindt u ze behulpzaam?
Wat zou er volgens u beterkunnen?
- Heeft u bij het indienen van een vraag het gevoel dat u veel moeite moet doen om geholpen te worden? Waarom wel of niet? (customer effort)

3. Waardering van het hybride supportmodel
- Hoe waardeert u de snelheid waarmee uw probleem meestal wordt opgepakt en opgelost binnen dit hybride systeem? (speed of resolution)
- Als u terugdenkt aan de laatste keren dat u contact had met de supportafdeling: waren de oplossingen die u kreeg bruikbaar en inhoudelijk juist? (correctness of the solution)

- Had u tijdens het gehele proces – van AI tot medewerker – het gevoel dat men u echt begreep en serieus nam? (feeling understood)
- Hoe heeft u de overgang van AI naar een menselijke medewerker ervaren? Verliep dit soepel, of moest u bijvoorbeeld informatie herhalen? (seamless transition)
- Heeft u ook de vorige versie gebruikt? Zo ja, wat is volgens u verbeterd of verslechterd?

4. Beleving van klantondersteuning
- Kunt u een situatie noemen waarin u zich gefrustreerd voelde tijdens het proces?

5. Rol van AI en medewerkers
- Hoe ervaart u de interactie met de medewerker nadat u de instuurhulp heeft doorlopen?

6. Reflectie op huidige werkwijze
- Als u terugkijkt op het gehele supportproces, van het moment dat u een vraag heeft tot aan de oplossing, hoe ervaart u dit als geheel? (2. Experience)
- Wat zou u veranderen aan de manier waarop klantondersteuning momenteel is ingericht bij AFAS? (3. Wishes and needs for future)

7. Afsluiting
- Is er nog iets dat u verder belangrijk vindt om te delen over uw ervaring met de Support van AFAS?

Appendix 4: ChatGPT Prompt analysis logs

You are a qualitative researcher conducting a thematic analysis of customer feedback logs collected after the use of a hybrid customer service system. In this system, each customer first goes through an AI-assisted support phase (such as a chatbot or automated suggestions), followed by contact with a human agent if the issue is not resolved.

The dataset consists of short open-text responses, a numerical satisfaction rating (1–5), and the submission date.

Objectives of the analysis:

1. Identify which aspects of customer service (such as speed, clarity, empathy, accessibility, autonomy) are most influential in shaping customer satisfaction or dissatisfaction.
2. Gain insight into how customers perceive the role of AI within this process.
3. Investigate whether there is a trend in customer satisfaction over time.
4. Make these insights useful for triangulation with interview data in a qualitative case study.

Analysis instructions:

1. **Theme-based clustering**: Group all responses according to the following themes:
    - Speed of support
    - Correctness of solution
    - Feeling of being understood
    - Customer effort
    - Smooth transition to employee
    - General frustration with AI
    - Positive experiences with AI
2. **For each theme**:
    - How frequently does this theme occur approximately?
    - What is the ratio of positive to negative remarks regarding this theme?
    - What are the most recurring comments or phrasings?
    - Are there clear signals about the role of AI or human assistance within this theme?
3. **Trend analysis of customer satisfaction (scores)**:
    - Analyse whether the average customer satisfaction score has increased, remained stable, or declined over time.

- Use the submission date, preferably aggregated by month or quarter.
- Highlight notable peaks or drops and any explanations mentioned in the feedback.

4. **Reporting format**:
   - Present the analysis theme by theme
   - Include representative quotes where appropriate
   - Provide quantitative estimates (number of mentions, percentage positive/negative)
   - Add a brief summary of the overall development in satisfaction over time

Use a clear, research-oriented writing style so that the output can be directly applied within a thesis context.

Appendix 5: Results interviews 1/2

Participant	Speed of resolution	Correctness of solution	Feeling understood	Customer effort	Seamless transition
R1, experienced customer Negative Astrid	“It works well for simple questions, but there is a delay for complex questions”	“I often feel misunderstood by a chatbot and articles often do not match”	“Sometimes the language used is very technical and that is annoying”	“It takes a lot of effort to get through the submission help”	“After completing the form, the employee do have all the necessary knowledge, that’s nice”
R2 Experienced customer Rik	“I think the speed of handling an incident is about the same as the previous version”	“The articles often cover the basics and make you understand things but it often doesn't solve the problem”	“I don't feel empathy from a chatbot, which is necessary if you have a software problem that your company is very dependent on”	“the hybrid model is cumbersome and customers have to put more energy into it”	“It is more pleasant for employees to find out first and only call when the answer has been found”
R3 Experienced customer Mees Positive	“I often figure it out on my own with help articles and if not, I am satisfied with the response time in most cases”	“In 90% of the cases I can find my answer in articles. This has improved significantly over the years”	“Sometimes I miss the completeness in answers. So just get multiple options where the problem could be”	“it takes a little more effort to finally speak to an employee”	“I like the fact that when I speak to an employee on the phone, he already knows what he is talking about and I don't have to explain it anymore”
R4 Experienced customer Jaap	“I don't think the speed of response is that great. I think it often takes quite a long time and then it irritates because you want to continue”	“The basics articles can be relevant to refresh things. But for complex questions it is not complete enough and is human expertise needed”	“Sometimes I feel like the AI tools don't look at what I actually wrote”	“These are just extra steps you have to take as a customer, so it also takes more time.”	“The employee has already been able to find out some things himself based on what I sent in. So it can be processed faster that way”
R5 Experienced customer Vincent	“The current speed at which an incident is resolved slower than before with the traditional method”	”In some situations it is fine if a chatbot or help articles provide the right answers, but in most cases they are not yet trained to actually solve the problem”	“The employees really try to think along with the problem while the AI tools generate their answers based on data. So you notice that as a customer”	“You have to take extra steps, define the problem and then the follow-up questions, the suggested articles that come up that customers are expected to read, all that kind of stuff”	“I notice that employees are often well informed about the problem and that you don't have to say much about it anymore”

R6 Experienced customer Ankie	“The speed of solving knowledge questions is more suitable for handling with the chatbot”	“I actually stick to my position that the AI steps never exactly address your specific problem”	“I think there are still too many mistakes in the interaction with AI”	“This current form of support where the AI implementations are becoming more visible costs me more effort”	“It's very frustrating when employees ask a question about something you literally put in your incident”
R7 Inexperienced customer Negative Eppo	In the past, when you could immediately speak to someone on the phone, complex problems were solved more quickly	“I have not yet been able to find a solution based on articles generated with AI”	“An employee shows empathy and is therefore more pleasant. AI tools feels distant”	“you have to go through many more steps because of the AI implementations ”	“It's ridiculous that you have to pay to be able to speak directly to an employee”
R8 Inexperienced customer Brenda	“if I ask a basic question that can be solved with a chatbot, it saves a lot of time for both parties”	“AI tools are suitable for knowledge questions that have faded away, but in 90% of cases you need an employee to solve them because of its complexity”	“It has become a bit more impersonal and it seems as if the focus has shifted from customer-oriented to a more massive handling of as many incidents as possible”	“These AI steps are sometimes useful because I don't always have to file an incident because I can solve it independently. In that case it costs me less effort”	“I don’t know actually”
R9 Inexperienced customer Willem	“What I like is that I often get an answer directly via AI such as the chatbot or the knowledge base that I can use. That saves time, especially with the simpler questions”	“The chatbot itself often provides useful links to help articles or step-by-step plans for simple questions, but that does depend largely on how I formulate my question.”	“Contact via a chatbot is of course somewhat distant. As soon as my question is taken over by an employee, I notice that they really think along with me”	“In general, that's not too bad. The customer portal is quite logically structured and I now know pretty well where to go if I have a question”	“In most cases quite smooth. My previous steps usually automatically forwarded to the employee”
R10 Inexperienced customer Sabine	“For layout questions, it often takes a very long time but for other questions I often get quick answers”	“Often, relevant articles are generally shown but it often just does not fit my specific problem”	“A chatbot is often fine to start with but if it doesn't answer your question you just don't feel understood”	“It takes a bit more effort because of the extra steps but personally find this manageable”	“It would be nice to keep the option to switch to an employee yourself”

R11 Inexperienced customer Jochem	“it seems that incidents are resolved faster, probably because fewer queries are passed on to staff because they can be resolved with AI”	“For simple questions, this is effective but it sometimes remains unclear whether a question is complex enough to call in a staff member for this”	“from a chatbot, there does lack some form of understanding if you can't quite figure something out and then you just want to call someone”	“More is expected of customers' independence to solve certain questions themselves and that does take more time”	“all the information you put down ends up in the incident and can always be viewed by yourself as well as the employee. I therefore think this set-up is fine”
R12 Inexperienced customer Sam	“if you make it very accessible for everyone to send in incidents they haven't looked at themselves the capacity probably can't handle it”	The articles do not always fit the problem but then that is what staff are for	“The chatbot does not yet work so well that it can replace all human work and empathise with the customer's problem in the same way”	“It makes sense to me that the customer does not just send in an incident without putting in some effort himself first.”	“everything will be in the incident in such a way that the employee can start working on it immediately without having to request more information”

Appendix 6: Results interviews 2/2

Expectations, experiences, and future needs experienced customers

First-order concept	First-order code	Second-order theme	Aggregate dimension
"I think the speed of resolution is the most important" (R1)	Response speed	Most important Customer Support Factors (unprompted response)	Perceived service quality experienced users towards hybrid support model in software company
Understand what you are talking about. So the knowledge of the Support employees (R2)	Knowledge of employees		
"I think the response time is the most important. It also depends on the urgency of the problem" (R3)	Response speed		
"I think speed is the most important thing. If you get stuck, you want to be able to continue as quickly as possible. And also that you get a clear and complete answer" (R4)	Response speed and completeness answers		
"The speed because when you are busy at that moment, you want it to be resolved as quickly as possible" (R5)	Response speed		
"That you can easily submit an accident" (R6)	Accessibility		
"I find it annoying that I have to go through so many steps before I can speak to an employee" (R1)	Barrier created by AI	Current experience of the hybrid support model (unprompted response)	
"Experience it as a brake or hindrance to send something in" (R2)	Barrier created by AI		
"Generally fine, there are some errors which cause minor irritation but current setup understandable from AFAS point of view" (R3)	Customer tolerance of system imperfections		
"It feels a bit like a blockage to get in touch with an employee" (R4)	Barrier created by AI		
"It feels a bit like a firewall. It seems that AFAS wants as much as possible to be handled without intervention" (R5)	Barrier created by AI		
"It's a lot of double work that you have to do" (R6)	Barrier created by AI		
"It would be nice if you could immediately determine from the type of question whether it is complex or can be solved with a chatbot" (R1)	Recognizing complex incidents and give faster route	Future needs and wishes regarding to Customer Support (unprompted response)	
"I would not give this hindrance to those who submit it correctly, but rather reward them for doing it well" (R2)	Give people who do things right a faster route		
"Could be adjusted to customer profile but if it ensures faster processing, there's no problem" (R3)	Give people who do things		

	right a faster route		
"It is important that customer support remains easily accessible by telephone every day" (R4)	Telephone contact remains crucial		
"It would be nice if the option to directly brainstorm with employees remained" (R5)	Telephone contact remains crucial		
"That all tools for people who do not wish to submit incidents are adapted to people who do not submit incidents very often" (R6)	Give people who do things right a faster route		

Expectations, experiences, and future needs inexperienced customers

First-order concept	First-order code	Second-order theme	Aggregate dimension
"I think it is most important that they are easily accessible and that there is sufficient knowledge (R7)	Accessibility and knowledge	Most important Customer Support Factors (unprompted response)	Perceived service quality inexperienced customers towards Hybrid Support model in software company (unprompted response)
"I find a clear, transparent explanation most important. I also want to understand what the cause of this is" (R8)	Clear communication		
"In most cases the speed of resolution" (R9)	Speed of resolution		
"Find it especially important to communicate clearly" (R10)	Clear communication		
"I think the most important aspect is that you are treated with understanding and empathy" (R11)	Clear and understanding communication		
"My problem should be taken seriously if I cannot find my answer with a chatbot and communicate in understandable language" (R12)	Clear communication and being taken seriously		
"It seems a bit like AFAS wants to keep the door closed to personal contact" (R7)	Barrier created by AI	Current experience of the hybrid support model (unprompted response)	
"It's nice that there are a lot of help tools offered, but in some cases I think it goes a bit too far" (R8)	Too much dependent of AI tools		
"Comes across as unprofessional if the AI tools don't work" (R9)	Unprofessional when AI tools don't work		
"You will be better guided by AI tools before you interact with an employee" (R10)	Better guided because of AI tools		
"I think it works fine in itself because as a customer you get some more tools to find the answer yourself" (R11)	better tools to solve things independently		

“I like the fact that through AI you sometimes already get an answer to your question and so don't necessarily have to speak to an employee “ (R12)	AI can answer questions without needing to speak employees		
“I would make it accessible in principle and people who really abuse it should just be dealt with in that way” (R7)	Give people who do things right a faster route	Future needs and wishes regarding to Customer Support (unprompted response)	
“If something is a priority, I want it to be resolved as quickly as possible, and the intermediate steps don't really help. I want to be in touch with an employee as soon as possible (R8)	Telephone contact remains crucial		
“I sometimes want to spend less time on this, even though this is part of my current job, it is something I don't plan time for in my weekly planning, for example” (R9)	make it less time consuming from a customer perspective		
“Not to go overboard with the use of chatbots and the like, and in complex situations, personal contact is crucial (R10	Personal contact remains crucial when issue is complex		
“Ensure that customers can choose how they want to get in touch with customer support” (R11)	give customers a choice in how they want to get in touch		
“I do hope it remains accessible to get in touch with employees if it cannot be resolved by a chatbot “ (R12)	Personal contact remains crucial		