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Exploring the behavioural intention of salespeople in selling ai solutions

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EXPLORING THE BEHAVIOURAL INTENTION OF SALESPEOPLE IN SELLING AI SOLUTIONS

MASTER THESIS

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Abstract

This study focuses on how the behavioural intention of a salesperson in a market research organisation to present an AI solution to customers can be improved. In doing so, the Theory of Reasoned Action (TRA) was used to assess the salesperson's attitude towards the AI solution affecting their behavioural intention to engage in such behaviour. Furthermore, underlying factors shaping the salesperson's attitude were investigated by integrating influences of human behaviour and AI adoption. Accordingly, a conceptual model with corresponding hypotheses was formulated, which contained social factors, the salesperson's characteristics, and product-related factors affecting a salesperson's attitude and behavioural intention. Through a questionnaire sent to 198 employees from the Sales-, GTIC- and Research departments, 104 completed questionnaires were collected. After the data collection, multiple regression analyses were conducted to test the conceptual model and hypotheses.

The results revealed that a salesperson's perceived accuracy of the outcomes provided by the AI solutions and subjective norm positively influenced their attitude towards the AI solution, in which perceived accuracy is the most vital driver, enhancing their behavioural intention to present it to customers. Besides, this research found that improving a salesperson's attitude towards an AI solution and their behavioural intention to present it depends on how AI technology is employed to compose an AI solution. The results showed that a salesperson's awareness and relative advantage positively and significantly directly affect their attitude, depending on the AI solution. Furthermore, customer stewardship and customer knowledge showed distinct moderating effects on a salesperson's behavioural intention depending on the AI solution. This research recommends that Market research organisations should focus primarily on increasing the salesperson's attitude to improve their behavioural intention to present an AI solution to customers. They could do this by focusing on changing a salesperson's perception of the solutions to increase their attitude by promoting transparency through training- and trial sessions. Besides, due to the additional insights varying on the type of AI solution, it is essential to note that market research organisations must indicate how AI technology is used to compose the solution before considering other actions. Specifically, they should deal with a salesperson's customer stewardship by differentiating the level of their customer stewardship for each customer and focusing on these types of customers, which would increase the attitude and behavioural intention of the salespersons.

Key words: Behavioural intention, attitude, salesperson's selling behaviour, solution selling, AI adoption, AI readiness, awareness, perceived accuracy, social influence, customer stewardship.

Executive summary

Introduction

In today's changing business environment with increasing competition and more demanding customers, market research organisations must innovate continuously to create a competitive advantage and add more customer value. Hence, market research organisations are introducing innovative and more efficient solutions supported by Artificial Intelligence (AI) to add to their existing solutions portfolio to enhance quality, speed, and innovation in traditional market research approaches. Although acting on their increasing interest in adding these AI solutions to their portfolio, market research organisations experience that their salespeople are reluctant in introducing these solutions to customers and lack to see the potential benefits of the AI solutions.

To realise value from these new AI solutions, a salesperson must introduce and present them to their customers during the sales process. Thus, by adding new solutions to the portfolio, salespeople must constantly decide whether to sell a well-known solution or one that is new to the market and the salesperson, which carries some risk and outcome uncertainty (Van der Borgh & Schepers, 2018).

Due to this reluctance and untapped potential benefits of the AI solutions, understanding the differences in salespeople's behavioural decisions is interesting to investigate. Several studies examine such behavioural decisions of individuals in different contexts by examining the individual's attitude that affects the behavioural intention (Cao et al., 2021; Chawla & Joshi, 2019; Chua et al., 2023).

This research examines a salesperson's behavioural intention to present an AI solution by investigating the underlying factors shaping a salesperson's attitude towards the AI solution integrating influences of human behaviour and AI adoption. This resulted in the following research question to serve the aim of this research:

How can the behavioural intention of a salesperson in a market research organisation to present an AI solution to customers be improved?

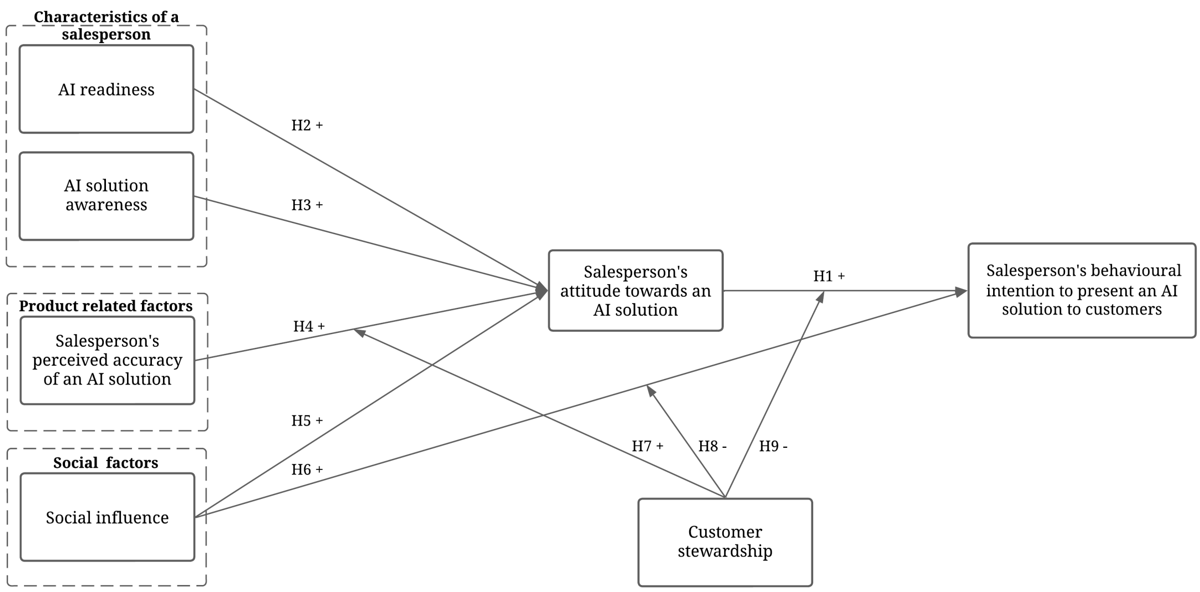
This master thesis results from a project carried out at MetrixLab B.V., a global digital research organisation providing marketing analytics and consumer insights that drive business decisions in a business-to-business context. They have two distinct AI solutions in its solution suite, which differ in their use of AI technology: ACT Instant and Immerse. Whereas ACT Instant uses AI's machine learning elements to generate outcomes, Immerse uses a discussion platform's AI technology to analyse human responses of large groups in real-time.

MetrixLab experiences that sales of their AI solutions are lagging and that only a few salespeople offer it to their customers. In particular, the solutions in which AI algorithms are an indispensable element to predict advertising success without human input through surveys, such as ACT Instant, are not that popular in sales. They are interested in getting future insights for improving a salesperson's willingness to present the possibility of an AI solution transparently when informing the customer of all suitable solutions in the sales process.

Conceptual Model

This research used the Theory of Reasoned Action (TRA) of Fishbein and Ajzen (1975) as a fundamental base for investigating the underlying factors that shape a salesperson's behavioural intention to present an AI solution to a customer. However, as TRA does not include antecedents in how the salesperson's attitude is formed, constructs derived from AI adoption and solution selling are incorporated to investigate the antecedents of a salesperson's attitude. Hence, besides the salesperson's attitude and social factors, the conceptual model focused on the salesperson's characteristics and product-related factors. Moreover, a part of a salesperson's role is maintaining a continuous and trusting relationship with their customers, thus the moderating effect of customer stewardship is included in the conceptual model. Figure 1 depicts the conceptual model of this research, including the corresponding hypotheses.

Figure 1 - Conceptual model of the research



Methodology

This research had a mixed methods design. This research dominantly used a quantitative research method; qualitative research functioned for identifying and shaping the problem definition by conducting unstructured exploratory interviews.

The data was collected via an online questionnaire sent to 198 employees from the Sales-, GTIC-, and Research departments, from which 104 individuals completed the questionnaire. Before the questionnaire was sent, it was tested among employees outside the sample. This changed the approach in which the sample was tested on both solutions, as they mentioned that they would answer differently depending on the solution. The items for behavioural intention, attitude, and perceived accuracy were disaggregated, leading to the hypotheses being tested separately on both solutions. The data is analysed using multiple regression, mediation and moderation analyses in SPSS Statistics using PROCESS Macro to test the proposed hypotheses for both solutions, and the similarities and differences were compared. Afterwards, further analysis with exploratory variables was conducted to investigate potential relationships or uncover unexpected insights.

Results and Discussion

Consistent with the fundamental tenet of the TRA framework (Damerji & Salimi, 2021), the results suggest that attitude towards an AI solution has a positive association with behavioural intention to present it. Further, the results showed that a salesperson's perceived accuracy of the outcomes provided by the AI solutions and subjective norm positively influenced this attitude towards the AI solution, in which perceived accuracy of the AI solution acts as the strongest driver. Contrary to expectations of social influence, only subjective norm significantly positively affects a salesperson's attitude towards the AI solution, and social identity did not significantly affect their attitude. Moreover, the results showed that subjective norm is not directly related to a salesperson's behavioural intention to present an AI solution to the customer, suggesting a full mediation by attitude towards the AI solution. Furthermore, contradicting with literature (Damerji & Salimi, 2021; Flavián et al., 2022), the results showed that salesperson's AI readiness does not relate to their attitude towards an AI solution.

Besides similar results for both cases, testing the disaggregated hypotheses separately for both AI solutions also showed differences in a salesperson's awareness and relative advantage in case of significance. A salesperson's awareness and relative advantage positively and significantly affect their attitude towards Immerse, but not their attitude towards ACT Instant. Furthermore, customer stewardship moderately affects a salesperson's behavioural intention to present ACT Instant differently than their intention to present Immerse, suggesting that the role of customer stewardship depends on how AI technology is employed to compose the AI solution. These unexpected differences implicate the contrast between the importance of their accuracy perception for the two solutions. The various natures of the AI solutions imply that if a salesperson has a high customer stewardship level and the AI solution includes human input, their accuracy will less impact their attitude before they are willing to present the AI solution. However, suppose a salesperson has a high customer stewardship level, and the AI algorithms are indispensable in predicting the outcome, their attitude will be more critical. In that case, indirectly they should perceive a high accuracy before they are willing to present the AI solution. Besides further analysis of customer knowledge as a moderator, testing it on the same relationships as customer stewardship explained customer stewardship's contradicting and unexpected results. The long-term trusting relationship between the customer and salesperson described the effect of customer knowledge, which explained the effect of customer stewardship.

Managerial Implications

Because a salesperson's behavioural intention to present an AI solution is based on their attitude towards it, it is suggested to focus on increasing their attitude. As the perceived accuracy of a salesperson was found to have the most substantial effect on a salesperson's attitude, market research organisations should primarily focus on changing a salesperson's perception of the solutions by promoting transparency through training- and trial sessions. The sessions should create more evidence of the solution's accuracy and set new boundary conditions by showing them examples, trials or mock-up cases of the AI solutions. Furthermore, they could increase the actual accuracy of AI solutions instead of solely changing the salesperson's perception by adapting the solution based on feedback.

Moreover, this research found that improving a salesperson's attitude towards an AI solution and their behavioural intention to present it depends on how AI technology is employed to compose an AI solution. Therefore, market research organisations must indicate how AI technology is used to compose the solution before considering other actions and, especially, learn how to deal with a salesperson's customer stewardship. Since these differences between the use of AI technology are specific to MetrixLab's solutions, further recommendations will be presented towards MetrixLab. First, MetrixLab could deal with a salesperson's customer stewardship by differentiating the level of their customer stewardship for each customer. By identifying the level of customer stewardship for each customer, they can give direction to the salesperson on which customers they should present the AI solution. Second, an intermediate version of ACT Instant would be another suggestion for MetrixLab, as the transition to an AI solution in which AI algorithms are an indispensable element in predicting the outcomes seems too revolutionary for their salespeople.

Preface

This Master's Thesis report results from my final graduation project conducted at MetrixLab as part of my Master's in Innovation Management at Eindhoven University of Technology. Nine months of dedication were required to finalise this report. Looking back on these months, I can say that creating and conducting this research had its fair share of challenges. Nevertheless, it has been an exciting learning opportunity with personal, scientific, and academic growth. By completing this thesis, I would like to express my gratitude to those who supported me during this process.

First, the kindness, support, and willingness to help of MetrixLab's employees played a crucial role in completing this thesis. A special appreciation goes to Jolique Weelink and Carlijn Tummers, who helped me connect with the right people and provided additional support when needed. Furthermore, the weekly brainstorming meetings were precious, giving me new insights every time.

Second, I want to extend my thanks to both of my TU/e supervisors, Jeroen Schepers and Ed Nijssen. Particularly, I would like to thank Jeroen Schepers, my first supervisor, for his guidance through this process on an academic and personal level. His extensive and constructive feedback containing challenging questions, comprehensive answers, and other forms of advice, pushed me to learn more about myself and elevate my research to a more academic level. Furthermore, thanks to Ed Nijssen, who, as my second supervisor, provided valuable and substantive feedback in the final stages of my research.

Finally, I would like to thank my family and friends for their support through the sometimes-challenging times during this process. There were many ups and downs, but all of you supported me in never giving up and believing in myself to reach my goal. Therefore, I would like to show them my gratitude in this way.

Myrthe van Bergen
Eindhoven, July 2023

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1. Introduction

In today's changing business environment with increasing competition and more demanding customers, market research organisations must innovate continuously to create a competitive advantage and add more customer value. Due to this need to innovate continuously, market research organisations are introducing innovative and more efficient solutions supported by Artificial Intelligence (AI) to add to their existing solutions portfolio. AI benefits these organisations by lowering costs and enhancing quality, speed, and innovation in traditional market research approaches using surveys, interviews, focus groups, or customer observations.

While AI is not something new, market research organisations have recently become more interested in the possibilities (Enholm et al., 2022; Huang & Rust, 2020). Although acting on their increasing interest in adding these AI solutions to their portfolio, market research organisations experience that their salespeople are reluctant to introduce these solutions to customers and lack to see the potential benefits of the AI-supported solutions.

In business-to-business (B2B) markets, market research organisations provide insights into customer questions regarding making solid business decisions, determining new business opportunities, and avoiding business failures. These insights are provided by gathering and analysing data about a company's customers, competitors, distributors, or other market forces. They present these insights as a solution with personalised (strategic) advice tailored to the customer's question. So, in order to realise value from these new AI solutions, a salesperson must introduce and present them to their customers during the sales process. By adding new solutions to the portfolio, salespeople must constantly decide whether to sell a well-known solution or one new to the market and the salesperson, which carries some risk and outcome uncertainty (Van der Borgh & Schepers, 2018). This perceived risk and outcome uncertainty are possible causes of why market research organisations experience this reluctance from their salespeople.

Due to this reluctance and untapped potential benefits of AI solutions, understanding the differences in salespeople's behavioural decisions is interesting to investigate. Several studies examine such behavioural decisions of individuals in different contexts by examining the individual's attitude that affects behavioural intention (Cao et al., 2021; Chawla & Joshi, 2019; Chua et al., 2023). In this study, behavioural intention is defined as the willingness of a salesperson to present the AI solution to the customer (Mehta et al., 2022). This willingness to engage depends on the salesperson's attitude and subjective norms (Mehta et al., 2022). Hence, a salesperson makes behavioural decisions, such as choosing the best-perceived solution(s), depending on their attitude towards the solution.

As the salesperson chooses the best-perceived solution to solve the customer's need or problem (Pourmasoudi et al., 2022; Sharma et al., 2008), their adoption of the solutions could play a significant role in forming their attitude. Following the reasoning of adoption literature (Athuahene-Gima, 1997; Homburg et al., 2010), if the salesperson has adopted the specific solution, they are more familiar with its features, benefits, and applications, positively influencing their attitude and behavioural intention. Considering this research's focus on solutions supported by AI, the adoption of technology, specifically AI, is deemed significant as this could influence the salesperson's attitude towards the solutions affecting their decision-making process. Therefore, this research investigates the underlying factors that shape a salesperson's behavioural intention to present an AI solution to a customer by integrating influences of human behaviour and AI adoption.

1.1 Research Question

As mentioned in the previous section, this research examines a salesperson's behavioural intention to present an AI solution to customers. The following research question is formulated to serve the goal of this study:

How can the behavioural intention of a salesperson in a market research organisation to present an AI solution to customers be improved?

To answer this research question, this research collected data from the market research organisation MetrixLab, which will be introduced in Chapter 1.2. This section will also discuss their specific problem in detail, fitting the context explained in the introduction. Chapter 2 elaborates on the theoretical background focusing on human behaviour-, solution-selling-, and AI adoption literature. The literature review findings will be used to compile constructs for the proposed conceptual model and hypotheses, which will be presented in Chapter 3. Subsequently, Chapter 4 contains the methodology, demonstrating the research design, data collection, data analysis, and measuring constructs. Chapter 5 presents the results of the data analysis. Finally, Chapter 6 provides the interpretations of the results and the theoretical- and managerial implications but also discusses the research's limitations and suggestions for future research.

1.2 Empirical Context

1.2.1 Company Introduction

MetrixLab, headquartered in Rotterdam (The Netherlands) and founded in 1999, is a fast-growing global digital research company. The company employs nearly 1000 people in 23 countries worldwide. MetrixLab provides marketing analytics and consumer insights that drive business decisions for global and local brands such as Unilever, Mondelēz International, Heineken, and Bayer. The four central departments within MetrixLab are *Sales*, *Research*, *Corporate Management*, and *Global Technology, Innovation, and Consultancy* (GTIC). The GTIC team guided this current research.

1.2.2 Solution Introduction

MetrixLab has a range of solution suites, from creative testing to brand tracking and packaging to e-commerce optimisation. These suites are built to adapt to the customers' budgets, timelines, and business needs. This research focussed on two AI solutions, which vary in their role of using AI—varying from using AI without human input through surveys to get insights to using AI as a facilitator for analysing human input.

In 2019, MetrixLab launched an innovative AI solution named *ACT Instant* as an addition to its testing suite of solutions in the insight area of brand engagement. Whereas the previously established AI solution, called *Immerse*, uses a discussion platform's AI technology to make it possible to analyse the feedback of large groups of respondents in real-time, ACT Instant uses AI's machine learning elements to generate outcomes in combination with human insights expertise. ACT Instant does not require human input through surveys to predict advertising performance as traditional quantitative research solutions. ACT Instant has a small human element of analysing messages and emotions but depends on multiple AI algorithms as an indispensable element.

MetrixLab sees a high demand for AI solutions, such as Immerse, where AI technology is an additional feature to speed up data processing. However, the solutions in which AI algorithms are an indispensable element to predict advertising success without human input through surveys, such as ACT Instant, are not that popular in sales.

1.2.3 Research Scope

MetrixLab experiences that sales of their AI solutions are lagging, and only a few salespeople offer it to their customers. However, they are not interested in selling more AI solutions at the expense of the other solutions but interested in the salesperson informing the customer of all suitable solutions in the sales process and their willingness to include AI solutions. Additionally, they want the salesperson to transparently explain a customer the pros and cons of applying an AI solution to a customer's problem. MetrixLab has observed that employees have mixed opinions concerning the AI solution. Hence, they want to investigate the underlying factors that shape a salesperson's behavioural intention to present an AI solution to the customer. By unravelling and mapping out this problem, MetrixLab wants to get future insights for improving this process by introducing the possibility of an AI solution transparently.

2. Theoretical Background

In line with the stated research question, this chapter offers a comprehensive overview of the relevant literature associated with investigating a salesperson's behavioural intention to present AI solutions to customers. This chapter extends the literature discussed in the introduction, contributing to a deeper understanding of the factors driving this intention. To achieve this objective, the chapter is divided into three sections: Attitudes and behavioural intentions, the integration of technology adoption, and salesperson's characteristics in solution selling. Drawing upon relevant literature, the chapter will provide the theoretical foundation for creating the conceptual model and the corresponding hypotheses.

2.1 Attitudes and Behavioural Intentions

For understanding human behaviour, the Theory of Reasoned Action (TRA) of Fishbein and Ajzen (1975) is one of the most fundamental and influential theories that provide a theoretical framework. The TRA states that human behaviour is determined by an individual's behavioural intention to perform that behaviour (Fishbein & Ajzen, 1975). Various studies have used this theory to comprehend human behavioural intention in order to affect behaviours and decision processes (Damerji & Salimi, 2021; Mehta et al., 2022). Therefore, this theory is applied in this research to investigate the selling behavioural intention of a salesperson and predict their actions.

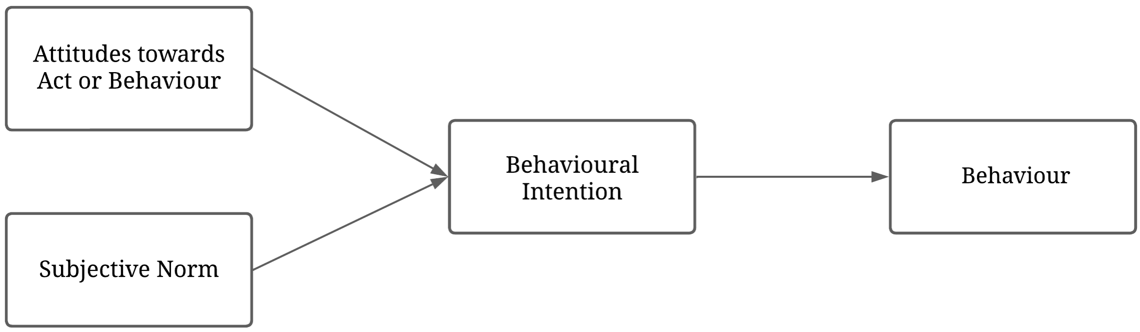
2.1.1 Theory of Reasoned Action (TRA)

Rooted in social psychology, the TRA examines predetermined factors influencing intentionally chosen behaviours. A fundamental tenet of the TRA is the idea that people's views of the consequences of a particular behaviour significantly impact their attitudes and perceptions and, subsequently, their intention to engage in that behaviour (Damerji & Salimi, 2021). This behavioural intention refers to an individual's willingness to perform a particular behaviour in the future. According to TRA, the stronger the intention is, the more likely the behaviour will occur. The intention to engage in such behaviours depends on one's attitude towards performing the behaviour and subjective norms, which are core constructs of the TRA (Mehta et al., 2022).

The construct "attitude towards act or behaviour" refers to an individual's evaluative effect, encompassing positive or negative feelings towards performing the target behaviour (Fishbein & Ajzen, 1975). These attitudes are based on an individual's beliefs and values, which influence their mental and emotional condition and how they think and feel about performing a specific behaviour, such as presenting a solution to a customer.

On the other hand, "subjective norm" is defined as an individual's perception of the beliefs held by significant others regarding whether they should or should not perform a particular behaviour (Fishbein & Ajzen, 1975). Subjective norms can feel like social pressures or social approval an individual perceives regarding a particular behaviour. These social pressures or approval include perceiving what significant others, such as family, friends, or colleagues, think about the behaviour (descriptive norms) and the motivation to meet the expectations of others (injunctive norms). TRA states that subjective norms also influence the intention to perform a behaviour (Fishbein & Ajzen, 1975). If a person feels that their social environment expects them to perform a particular behaviour, this will likely strengthen their behavioural intention. Figure 2 presents the original TRA framework, directly affecting behavioural intention and behaviour.

Figure 2 - The Theory of Reasoned Action (Fishbein & Ajzen, 1975)



By considering attitudes, and subjective norms, TRA is valuable as a fundamental base for investigating the underlying factors that shape a salesperson's behavioural intention to present an AI solution to a customer. However, TRA does not include antecedents in how an individual's attitude is formed. Therefore, other theories are reviewed to investigate underlying factors influencing the salesperson's attitude.

2.2 Integrating Technology Adoption

In this research context, the salesperson's selling behaviour is a decision-making process in which they choose the best-perceived solution for the customer, influenced by their attitude towards the solutions. In this decision-making process, they must consider whether to present a well-known solution or one new to the market and the salesperson. This complex decision between a known or a new solution involves their level of adoption of the new solutions (Van der Borgh & Schepers, 2018). Following the reasoning of adoption literature, if the salesperson has adopted the specific solution, they are more familiar with its features, benefits, and applications, positively influencing their attitude and behavioural intention. Besides, since the salespeople span the gap between the organisation and the possibly adopting customer, their adoption of the solution will likely be critical to the customers' adoption (Wieseke et al., 2008). Considering this research's focus on AI solutions, the adoption of AI technology is deemed significant as this could impact the salesperson's attitude towards the solutions affecting their decision-making process.

2.2.1 AI Adoption

Technology adoption literature examines individuals' decisions and behaviour to accept or reject new technology, such as AI. A widely considered and one of the most influential models to understand, explain and predict technology adoption is the Technology Acceptance Model (TAM) (Damerji & Salimi, 2021). Davis (1985) developed TAM to expand TRA regarding technology acceptance. TAM posits that the adoption and use of technology are primarily driven by two factors: "perceived usefulness" (i.e., the extent to which an individual believes that using the technology enhances their performance) and "perceived ease of use" (i.e., the degree to which a person thinks that using the technology requires little effort) (Schillewaert et al., 2005).

Various marketing literature studies have used TAM to explain human behaviour in sales regarding AI acceptance and adoption (Damerji & Salimi, 2021; Mehta et al., 2022; Schillewaert et al., 2005). However, the perceptive of this research and technology (or AI) adoption literature differ fundamentally from one another. Generally, literature on technology (or AI) adoption uses TAM to investigate individuals forming an opinion and perception on a technology influenced by diverse determinants, in which they decide whether they like it and will ultimately use it. However, this research focuses on a salesperson's technology adoption who must determine the solution's value for someone else, namely their customers. The salesperson adopts the solution outcomes only as a presenter or influencer. Therefore, since the salesperson is not using the AI technology, "perceived usefulness" needs to be approached differently and "perceived ease of use" will not be applicable for investigating the salesperson's attitude towards the AI solution. In the solution selling context, a salesperson must assess which solution would fulfil customer needs and preferences and enhance their performance. Considering this research focus on AI solutions, if the salesperson perceives that the AI solution can provide accurate information, they are more likely to believe that AI generates an enhanced solution, useful for the customer. Hence, TAM's "perceived usefulness" will be adapted to a salesperson's "perceived accuracy of the AI solution".

2.2.2 Adoption and Salesperson's Characteristics

Furthermore, various streams of research posit that personal characteristics are central to individuals' acceptance and adoption of technology. From this assumption, Parasuraman (2000) introduced the concept of technology readiness to measure if an individual is ready to adopt the technology. "Technology readiness" is defined as the people's predisposition to employ new technologies for completing goals in home life and at work (Parasuraman, 2000). It suggests that a person's perceptions of a particular technology can consist of positive and/or negative aspects, which jointly affect their tendency to accept and use new technology for accomplishing goals in life and at work (Damerji & Salimi, 2021). These aspects can be divided into four personality traits: optimism, inventiveness, discomfort, and insecurity, each measuring the extent of a person's openness to technology (Parasuraman, 2000; Parasuraman & Colby, 2015). The positive aspects will push people towards new technologies, and the negative aspects will pull them away (Parasuraman & Colby, 2015).

Optimism captures specific feelings and proposes that ‘technology is a good thing’. This personality trait is “a positive view of technology and a belief that it offers people increased control, flexibility and efficiency in their lives” (Parasuraman & Colby, 2015, p. 60). Innovativeness is “the tendency to be a technology pioneer and thought leader” (Parasuraman & Colby, 2015, p. 60). This personality trait measures how much people perceive themselves as leading in trying new technology.

Discomfort represents “a perceived lack of control over technology and a feeling of being overwhelmed by it” (Parasuraman & Colby, 2015, p. 60). People who experience discomfort have a general paranoia about technology-based services. Finally, insecurity refers to “the distrust of technology, stemming from scepticism about its ability to work properly and concerns about its potential harmful consequences” (Parasuraman & Colby, 2015, p. 60). Although it seems almost the same as discomfort, this dimension concentrates on specific elements of technology-based interactions rather than a general lack of comfort with the technology.

Combining these aspects creates an index indicating the degree of an individual’s technology readiness, influencing a salesperson’s acceptance and adoption. Because personality characteristics are viewed as significant factors in determining human behaviour and adoption of technology, and considering this research focus on AI solutions, “technology readiness” will be adapted to a salesperson’s “AI readiness”.

2.3 Salesperson’s Characteristics in Solution Selling

The previous subsection discussed the significant role of a salesperson’s characteristics from an adoption perspective; the following section will provide more details on the salesperson’s characteristics based on the selling process and their interaction with the customer. Since the salesperson decides the best-perceived solution for the customer, their characteristics are involved in the selling process for solutions. In the selling process, the salesperson’s characteristics entail a more in-depth understanding of the customer’s unique situation (Hoeber & Schaarschmidt, 2017) and strongly emphasises relationship orientations (Ulaga & Loveland, 2014). Besides, the salesperson’s solution adoption is driven by their observations and empathy with their customers, and they build their judgement on what is best for their customers (Wieseke et al., 2008).

2.3.1 Salesperson’s Reluctant Role in Solution Selling

Selling experience facilitates salespeople’s engagement in introducing new products/solutions due to gained skills and knowledge related to practical selling approaches, situations, and customers (Salonen et al., 2021). However, despite this selling experience, salespeople must constantly decide whether to sell a well-known solution or one new to the market and the salesperson, which carries some risk and outcome uncertainty (Van der Borgh & Schepers, 2018). This perceived risk reflects the ambiguity about whether the solution will provide potentially significant or disappointing outcomes. Assuming that salespeople are naturally risk averse, van der Borgh and Schepers (2018) claim that the more outcome uncertainty surrounding a behavioural choice, the more likely a salesperson favours the less uncertain well-established solution option. Furthermore, Ulaga and Kohli (2018) addressed that in the selling process, various uncertainties affecting salespeople primarily centre around customer needs and the solution's performance outcome, especially when it is new to the market and the salesperson. For example, a salesperson may be unaware of how to best position the solution in the market or communicate its' value to the customer or be unaware of how to assess the solution's performance and whether an alternative solution using different technologies might have produced better results (Ulaga & Kohli, 2018). Therefore, when dealing with new products, like AI technology, in solution selling, maintaining product awareness and knowledge is crucial for understanding and addressing the customer's problems. This is crucial as a salesperson's role regarding a solution's outcome entails assuring a customer that the solution will work to deliver the desired outcome (Ulaga & Kohli, 2018).

2.3.2 Salesperson-Customer Relationship

In selling solutions, salespeople manage customer relationships by taking a long-term, holistic approach, creating mutually beneficial and sustainable relationships. Therefore, part of a salesperson's role is maintaining a continuous and trusting relationship with their customers. Hoeber and Schaarschidt (2017) pointed out mutual trust as a critical criterion for strengthening long-term business relationships between provider and their customers. Therefore, a salesperson must assure customers that the solution's components will deliver the desired outcome. Consequently, the salesperson is more focused on offering the best possible solution to their customer's needs and preferences as they do not what to jeopardise the relationship. This focus makes a salesperson feel responsible for solving customers' problems and fulfilling their needs and preferences since customers make business decisions based on the recommended solution outcomes (Koponen et al., 2019). This feeling or responsibility aligns with the concept of "customer stewardship" introduced by Schepers et al. (2012), which is the degree to which a salesperson has a sense of ownership and feels morally responsible for a customer's overall welfare. A sense of ownership and responsibility is the belief that the customer and the services offered belong to the salesperson. This belief results in salespeople always taking all reasonable steps to ensure improved service delivery, emphasising that they consider themselves accountable for providing excellent service and actively working towards improving it (Boateng et al., 2022). This sense of ownership further stimulates the customer-focused efforts of the salesperson. Furthermore, customer stewardship is based on the idea that a company's success is closely tied to the success of its customers and that by investing in their well-being, a company can ultimately benefit as well (Boateng et al., 2022). This is why customer stewardship will be investigated in this research.

3. Conceptual Model and Hypotheses

The previous chapter presented various theories and models explaining human behaviour, AI adoption, and salesperson's characteristics in solution selling. After thoroughly examining and reviewing these theories and models and considering the context of selling AI solutions, this chapter presents a new conceptual model based on the original framework of TRA (Fishbein & Ajzen, 1975). TRA is used as a fundamental base to investigate the underlying factors that shape a salesperson's behavioural intention. However, as TRA does not include antecedents in how the salesperson's attitude is formed, constructs derived from AI adoption and solution selling are incorporated to investigate underlying factors that influence the salesperson's attitude. Hence, besides the salesperson's attitude and social factors, the conceptual model focuses on the salesperson's characteristics and product-related factors. Accordingly, hypotheses were formulated to examine the reasons behind a salesperson's attitude towards the AI solution and its effect on their behavioural intention to present it to the customer.

Chapters 3.1 and 3.2 will demonstrate the hypotheses for the direct and moderating effects based on the literature of the previous chapter. Moreover, the preliminary interviews with four MetrixLab employees showed the significant role of the salesperson's characteristics and the AI adoption process. Hence, some additional quotes are presented in these chapters to illustrate the fit of these constructs with the research context and the organisation. Finally, Chapter 3.3 will present the proposed conceptual model and an overview of the hypotheses.

3.1 Hypotheses Development for Direct Effects

3.1.1 Salesperson's Attitude towards an AI Solution

TRA states that the intention to engage in a particular behaviour depends on an individual's attitude towards performing the behaviour (Fishbein & Ajzen, 1975; Mehta et al., 2022). Slightly different from the construct attitude towards behaviour, this research focuses on a salesperson's attitude towards a technological item, like the AI solution, as this is part of the salesperson's decision process to engage in their selling behaviour.

Prior research studies concerning technology adoption have consistently found that attitude towards technology drives behavioural intention to adopt and use technology (Cao et al., 2021; Chawla & Joshi, 2019). Van Gool et al. (2015) could explain this finding by people's intrinsic motivation to maintain consistency between their attitudes and behaviours. So, a positive attitude towards technology is strongly associated with a higher behavioural intention to adopt and use the technology and vice versa. Literature on technology adoption primarily concerns the use of technology. As mentioned, the salesperson in this research acts not as an adopter and user but as a presenter or influencer for the customer. Hence, this research combines 'attitude towards behaviour' from the original TRA framework with 'attitude towards technology' from TAM.

Consistent with the definitions of 'attitude' in these several research studies, this study defines *attitude toward the AI solution* as the degree to which a salesperson judges the AI solution favourably or unfavourably for their customer (Chua et al., 2023). According to Fishbein and Ajzen (1975), attitude towards an item, concept or behaviour can impact an eventual action because they are fundamentally concerned with evaluating this along a dimension of favour or disfavour, good or bad, like or dislike. Hence, salespeople with a favourable judgement of AI could be more willing to present the AI solution to the potential customer. Accordingly, the following is hypothesised:

H1: Salesperson's attitude towards the AI solution positively affects their behavioural intention to present it to the customer.

3.1.2 Salesperson's AI Readiness

Management and marketing studies view personality characteristics, such as technology readiness, as significant factors in determining human behaviour (Damerji & Salimi, 2021). The theoretical background already emphasised the essence of considering technology, specifically AI, adoption since this is part of the salesperson's decision-making process. Adding to the significance of individuals' personal characteristics in adopting technology, the interviews raised additional concerns regarding the employees' readiness to embrace AI technology used in the solutions. The following quote illustrates this concern:

> *"I think ACT Instant might be more thrilling and tense for us. […] and I think everyone is too attached to the survey solutions that frequently sell." (Salesperson 4)*

"AI readiness", modified from Parasuraman (2000), is defined in this research as the people's predisposition to employ AI technology for completing goals in home life and at work. Flavián et al. (2022) mentioned that people's responses to technology are diverse due to the emotions that technology elicits, favourable and unfavourable. Therefore, if a salesperson responds to AI favourably, meaning that they are optimistic towards AI and have a higher level of innovativeness (the contributors dominate), they will have a positive attitude towards the AI solution. Accordingly, the following hypothesis is proposed:

H2: Salesperson's AI readiness positively affects their attitude towards the AI solution.

3.1.3 Salesperson's AI Solution Awareness

The AI-generated outcomes can be seen as "a new product" part of the solution since the salesperson interprets these outcomes to present the advice as a solution to the customer. As mentioned, the decision-making process becomes riskier due to a salesperson's lack of practical experience and awareness regarding the features (Athuahene-Gima, 1997). Besides, the lack of transparency and the "black-box" nature of AI algorithms can hinder an individual's ability to understand the reasoning behind the model's predictions, creating doubts and difficulties in accepting them (Shin, 2021).

"Awareness", in this research context, refers to the degree to which an individual is "conscious of, having knowledge of, or being informed about" a solution (Crist et al., 2007, p. 212). In line with Ulaga and Kohli (2018) and Shin (2021), the interviews showed a lack of awareness among the interviewees of assessing the solution's performance and understanding the reasoning behind the model's predictions, creating doubts. The following quote illustrates that the interviewee doubts ACT Instant:

> *"[...] as market researchers, we answer questions where no answers exist yet. Otherwise, customers could also buy a book, and then they will read the book and find an answer. So, it always concerns questions wherefore no answer exists yet. Therefore, I doubt that AI can give these answers because for entering the input into the solution, you should always have thought about the answer beforehand since AI must take into account everything, actually the whole world, to find that one answer relevant to that situation." (Salesperson 2)*

Furthermore, in technology adoption, awareness plays a vital role in shaping individuals' perceptions and attitudes towards new technological offerings. It is a foundation for understanding and evaluating the solution's benefits, features, and potential value, which can positively impact their acceptance and adoption decisions, which aligns with TAM (Davis, 1985). Specifically, in this research context, this comprehensive understanding allows salespersons to evaluate the solution's usefulness and effectiveness in addressing customer needs and enhancing sales performance, ultimately positively influencing their attitude.

H3: Salesperson's awareness of the AI solution positively affects their attitude towards it.

3.1.4 Salesperson's Perceived Accuracy of AI Solution

"Perceived accuracy" refers to the degree to which an individual's perception that a product, service, or solution would provide accurate information for decision-making purposes (Zhu et al., 2014). This concept is derived from TAM's perceived usefulness (Davis, 1985) and adapted to fit the solution-selling context. A salesperson must assess which solution provides an outcome that would fulfil customer needs and preferences and enhance their performance. Therefore, the salesperson must consider whether the AI solution can provide accurate information that meets customer needs and preferences. Moreover, interviewees expressed concerns about the shortcomings of the accuracy of the AI solution and a lack of trust in its outcomes. The following quotes illustrate this notion:

> *"In my example, the commercial contained much emotion and storytelling. It was one of those tearjerkers of a commercial, so to speak, which was a success because of these features. However, in our AI model, there is no room for that, and you cannot extract that. So, suppose we tested that commercial with ACT Instant, then ACT Instant would provide*

a bad outcome, and I would have presented an entirely wrong recommendation." (Salesperson 1)

"Immerse may also provide pretty flat results, but I am confident that the AI is much quicker in analysing all those responses and summarising the answers quickly. But, for ACT Instant, it is much more of what is being coded beforehand and is limited to what information we can put in. So, garbage in is garbage out." (Salesperson 2)

Supporting these quotes, Bedué and Fritzsche (2022) emphasise that due to the complexity of AI algorithms, individuals could find it challenging to understand how the AI-based tool constructs their predictions or decisions, making it difficult to trust in the obtained results. Hence, concerning the AI solution, a positive relationship is expected between a salesperson's perceived accuracy of its outcomes and their attitude towards the solution.

Besides, Zhu et al. (2014) demonstrate that inaccurate recommendations or information will irritate individuals and thus negatively impact their attitudes. Therefore, if the salesperson perceives the AI solution as providing inaccurate outcomes and predictions, it can negatively change their attitude. They may view the tool as an inadequate resource that hinders their ability to fulfil customer needs effectively (Kim et al., 2021). Based on these considerations, it can be hypothesised that the salesperson's perceived accuracy of the AI solution influences their attitude. A higher perception of accuracy will result in a more positive attitude. In contrast, a perception of inaccuracy is likely to lead to a negative attitude, which proposes the following hypothesis:

H4: Salesperson's perceived accuracy of the AI solution's outcomes positively affects their attitude towards it.

3.1.5 Social Influence on a Salesperson

Theoretical frameworks and models that explain and investigate human behaviour incorporate the social context as a significant factor, such as the TRA framework, including the subjective norm influencing attitude and behavioural intention as a core construct (Fishbein & Ajzen, 1975). By considering the broader term "social influence", this study aims to understand the factors that shape a salesperson's behavioural intentions in solution selling and AI adoption. In the context of sales and technology, social influence has been explored by researchers (Agarwal & Prasad, 1998; Homburg et al., 2010). These articles highlight the importance of social influence in shaping employees' motivation to act in a particular behaviour. Furthermore, Agarwal and Prasad (1998) indicate that a salesperson is more inclined to adopt sales technology if their peers have accepted it. Similarly, Homburg et al. (2010) demonstrate that the adoption of technology by co-workers and superiors positively influences the extent to which subordinates adopt it.

Focused on attitude changes, Kelman (1958) proposed three processes for analysing social influence. The three processes include subjective norm (compliance), group norm (internalisation), and social identity (identification), in which specifically subjective norm and social identity focus on social interactions. Subjective norm indicates the perceived organisational, managerial, and social pressure on an individual to perform a particular behaviour (Cheung & Lee, 2010). So, in the research context, it occurs when a salesperson is prone to receiving a favourable response from peers or groups and, therefore, accepts the influences of others. Realising oneself as a group member and the emotional and evaluative relevance of that membership, such as assessing one's self-worth and being emotionally invested, are necessary for developing a sense of social identity (Cheung & Lee, 2010). This process can occur when a salesperson yields the influences of peers or groups to establish or preserve a satisfying relationship with them.

In this research context, various processes come into play when considering the impact of social influence. Consequently, this conceptual model extends beyond the inclusion of subjective norm from the TRA and incorporates the construct of social influence, combining the processes of subjective norm and social identity. Accordingly, the following hypotheses are proposed to examine the relationship between social influence and salesperson behaviour:

H5: The social influence of peers positively affects a salesperson's attitude towards the AI solution.

H6: The social influence of peers positively affects a salesperson's behavioural intention to present the AI solution to the customer.

3.2 Hypotheses Development for Moderation Effects

3.2.1 Customer Stewardship

Besides testing the direct relationships towards attitude and behavioural intention, customer stewardship is incorporated as a moderator. As mentioned, choosing the best-perceived solution to present to the customer is partially based on the salesperson's assessment of the customer's wants and needs. In solution selling, the salesperson is focused on creating mutual trust to build a long-term relationship with the customer (Hoeber & Schaarschmidt, 2017). This long-term relationship with the customer allows a salesperson to feel responsible for the customer's welfare and focuses on offering the best possible solution (Koponen et al., 2019). Moreover, in this specific research context, a bad outcome of a solution could harm the customer's welfare since the customer makes business decisions on the recommended solution by the salesperson. Thus, a salesperson would be concerned that an inaccurate solution would fail to satisfy the customer's needs and potentially jeopardise their relationship, which is illustrated in the following quote:

> *"For ACT Instant, I just must trust that the solution has no garbage, which may be very negatively stated. However, I am always quite careful, so to speak, because otherwise, there is immediate damage to the customer and reputational damage for me personally. So yes, I must trust the outcomes." (Salesperson 2).*

Besides, customer stewardship emphasises building customer trust and transparency (Hoeber & Schaarschmidt, 2017), in which effective customer stewardship involves being open, honest, responsive, and transparent. A salesperson with a high sense of ownership and feeling morally responsible for the customer is motivated to provide honest advice on the optimal solution, aiming to maintain a long-term relationship (Hoeber & Schaarschmidt, 2017). Consequently, the salesperson develops a greater sense of responsibility for ensuring that the solution meets the customer's needs and preferences, making them more focused on the accuracy of outcomes and predictions of the AI solution since accuracy is a critical factor in guaranteeing customer satisfaction (Zhu et al., 2014). In other words, when a salesperson feels responsible for their customer, then the accuracy of the AI solution becomes more critical in how they think and feel about the solution. They are only optimistic about the solution if it works accurately; otherwise, it is not a possible option for their customer. However, suppose they do not care about the customer and are just selling solutions. In that case, accuracy becomes less critical, and AI would be more the gimmick of the solution that drives their attitude. Therefore, a salesperson who perceives a higher level of customer stewardship may be more motivated to provide accurate recommendations to their customer's best interest, requiring them to prioritise the accuracy of the AI solution.

Furthermore, when a salesperson perceives a higher level of customer stewardship, they may feel a greater responsibility for acting in the customer's best interest rather than only attempting to sell them the solution to satisfy the interest of other people in the company (Schepers et al., 2012). Consequently, the salesperson may feel their responsibility to act for the customer's welfare outweighs any pressure exerted by co-workers and superiors to promote the AI solution. Therefore, the salesperson is less likely to be influenced by social pressures, reinforcing their commitment to the customer's welfare.

Moreover, a salesperson's attitude towards the AI solution becomes less critical when they feel morally responsible for the customer, as their customer's welfare precedes personal beliefs or preferences (Schepers et al., 2012). So, a salesperson can be very optimistic about the AI solution because of its' perceived possibilities and benefits but estimates that it might not give the best solution to the customer and, therefore, not act on their attitudes. This suggests that customer stewardship weakens the positive relationship between attitude and behavioural intention, indirectly reducing the impact of the underlying factors of a salesperson's attitude. Hence, the following hypotheses are proposed for investigating the moderating effects of customer stewardship:

H7: Customer stewardship moderates the positive relationship between a salesperson's perceived accuracy and their attitude towards the AI solution such that this relationship becomes stronger when a salesperson perceives a higher level of customer stewardship.

H8: Customer stewardship moderates the positive relationship between the social influence of peers and a salesperson's behavioural intention to present the AI solution to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.

H9: Customer stewardship moderates the positive relationship between a salesperson's attitude towards the AI solution and their behavioural intention to present it to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.

3.3 Conceptual Model

Figure 3 depicts the proposed conceptual model with the dependent variable of behavioural intention, and Table 1 presents the corresponding hypothesised relationships.

Figure 3 - Conceptual model

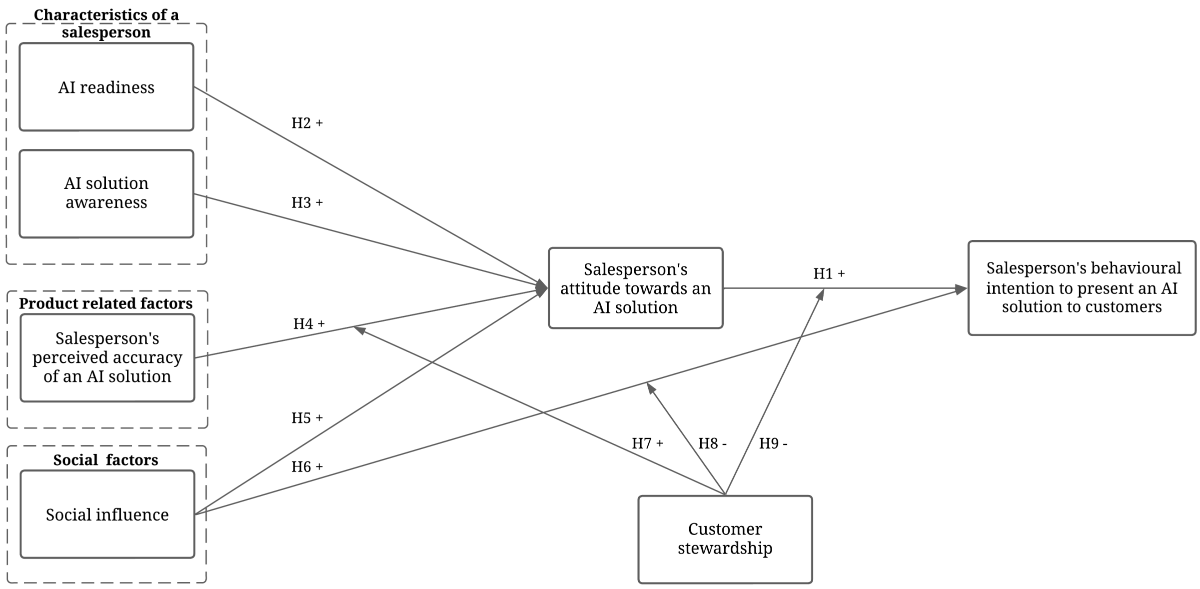


Table 1 - Overview of hypotheses

Hypotheses	
H1	Salesperson's attitude towards the AI solution positively affects their behavioural intention to present it to the customer.
H2	Salesperson's AI readiness positively affects their attitude towards the AI solution.
H3	Salesperson's awareness of the AI solution positively affects their attitude towards it.
H4	Salesperson's perceived accuracy of the AI solution's outcomes positively affects their attitude towards it.
H5	The social influence of peers positively affects a salesperson's attitude towards the AI solution.
H6	The social influence of peers positively affects a salesperson's behavioural intention to present the AI solution to the customer.
H7	Customer stewardship moderates the positive relationship between a salesperson's perceived accuracy and their attitude towards the AI solution such that this relationship becomes stronger when a salesperson perceives a higher level of customer stewardship.
H8	Customer stewardship moderates the positive relationship between the social influence of peers and a salesperson's behavioural intention to present the AI solution to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.
H9	Customer stewardship moderates the positive relationship between a salesperson's attitude towards the AI solution and their behavioural intention to present it to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.

4. Methodology

This chapter specifies the methodology used for this research, explaining the research design and the participants involved. Subsequently, the data collection, measures, strategies for assessing reliability and validity, and descriptive statistics will be discussed. Finally, the data analysis will be discussed in detail, including examining the data, correlations, and assumptions.

4.1 Research Design

This research had a mixed methods design, combining qualitative and quantitative data research methods. A mixed methods research design draws strengths from this combination of techniques, creating a more vital research outcome than either method individually (Johnson & Onwuegbuzie, 2004; Malina et al., 2011). This research dominantly used a quantitative research method; qualitative research functioned for identifying and shaping the problem definition by conducting unstructured exploratory interviews with four MetrixLab salespersons. The interviews included a list of topics from solution-selling and technology adoption literature to discuss. However, they did not have fixed questions, which provided flexibility in asking in-depth questions when a particular issue was more applicable than initially thought.

Moreover, the data was collected using a quantitative research method. Advantageous of the quantitative research method is using smaller groups of individuals to draw conclusions about larger groups that would be prohibitively expensive to research (Holton & Burnett, 1997). Since MetrixLab is a global company with employees in 23 countries worldwide, an online questionnaire was suitable for reaching as many respondents as possible, saving costs, reducing response time, eliminating interviewer bias, and creating time availability (Granello & Wheaton, 2004).

4.2 Participants

4.2.1 Sample

The population for the online questionnaire, which received an invitation link, is a total of 198 employees from the Sales-, GTIC-, and Research departments. Although it seemed logical to include only the Sales department in the sample, GTIC- and the research department were also included. At MetrixLab, GTIC consultants and the research department's senior research managers have considerable communication with (potential) customers. Furthermore, they are always present when communicating the solution options and very often do the presentations themselves. Hence, the population was carefully selected, including all departments involved in the sales process. This selection procedure is known as a purposive sampling strategy (Etikan, 2016).

Bartlett et al. (2001) discussed the importance of determining sample size within a quantitative questionnaire design, as the sample size can influence the detection of significant differences, relationships, or interactions. Therefore, the sample size was determined with Cochran's (1977)sample size formula for continuous data (Bartlett et al., 2001). According to this formula, the minimum return sample size of 74 respondents (See Appendix A). As 104 individuals completed the questionnaire, this value exceeded the minimum return sample size.

4.2.2 Increasing Response Rates

Despite the advantages of online questionnaires, the possibly occurring low response rate and non-response bias are disadvantages. A multi-mailer system was one of the actions attempted to raise the response rate. This system can send an email to multiple people simultaneously and still include a personal touch on each email. Additionally, studies have shown that response rates are consistently higher when an incentive is provided compared to no incentive (Sammut et al., 2021). Therefore, the email included information about the incentive for completing the online questionnaire. Appendix B presents the email format for the first invitation link.

The platform of MetrixLab precisely tracks the user IDs of the people who completed the questionnaire and who have not. By using this information, only those who had not completed the online questionnaire received a reminder email. Besides, using unique user IDs, the respondents could complete the questionnaire only once. After four days, a first personal reminder from one of the MetrixLab supervisors was sent to those who had not completed the questionnaire yet with an explanation and a convincing request to complete the questionnaire (see Appendix C). This request helped get a higher response rate than receiving it from a student/intern, for them, a less known person.

After six days, a second and final reminder was sent to people who had not completed the questionnaire yet. The response rate increased noticeably after sending multiple reminders, which reduced the problem of a lower response rate (Granello & Wheaton, 2004). All these actions resulted in a response rate of 52.53%. Table 2 presents relevant information regarding the respondents.

Table 2 - Descriptive statistics of demographic variables

Characteristic	Category	Frequencies (N= 104)
Gender	Female	43 (41.3%)
	Male	61 (58.7%)
Age	Average in years	42.2 (SD= 9.3)
Nationality	Asian Pacific	23 (22.1%)
	European	55 (52.9%)
	American	26 (25.0%)
Geographical region	Asia, Middle East, and Africa (AMEA)	22 (21.2%)
	Europe (EU)	49 (47.1%)
	Latin America (LATAM)	4 (3.8%)
	North America (NA)	29 (27.9%)
Department	Sales	67 (64.4%)
	GTIC	10 (9.6%)
	Research	27 (26.0%)
Involvement ACT Instant	Never	30 (28.8%)
	1 – 2 times	24 (23.1%)
	3 – 4 times	19 (18.3%)
	5 – 6 times	8 (7.7%)
	> 6 times	23 (22.1%)
Involvement Immerse	Never	14 (13.5%)
	1 – 2 times	16 (15.4%)
	3 – 4 times	12 (11.5%)
	5 – 6 times	12 (11.5%)
	> 6 times	50 (48.1%)
Work experience	0 – 5 years	6 (5.8%)
	6 – 11 years	27 (26.0%)
	> 11 years	71 (68.2%)
Sales experience	0 – 2 years	50 (48.1%)
	3 – 5 years	22 (21.2%)
	6 – 8 years	12 (11.5%)
	9 – 11 years	9 (8.7%)
	> 11 years	11 (10.6%)

Notes: Each respondent filled in the questionnaire for both AI solutions.

4.3 Data Collection

This research was conducted sequentially into an exploration-, investigation-, data analysis-, and evaluation phase (see Appendix D). The exploration and investigation phase intermingled. The exploration phase started by using the retrieved problem insights of MetrixLab to create the first version of the problem definition. Using unstructured exploratory interviews with MetrixLab employees, literature findings, and supervisor feedback, the necessary adjustments were identified to shape the problem definition. Accordingly, in the investigation phase, the literature findings were combined to compile the constructs and accompanying relationships resulting in the proposed conceptual model. The output of these interviews was used to illustrate the fit of these constructs with the research context. Several steps in these two phases were repeated several times, which helped execute the subsequent phases and reduced uncertainties and random errors.

The quantitative data analysis started with developing an online questionnaire. Afterwards, before the questionnaire was conducted among MetrixLab's employees, it was tested on flow, length, completeness, and comprehensiveness among five employees outside the sample population.

Accordingly, necessary adjustments were made. Subsequently, the questionnaire was sent out to the employees to gather data. The analyses were conducted in SPSS Statistics using the PROCESS Macro.

The qualitative and quantitative data analysis findings were evaluated and documented in the evaluation phase. These findings were combined to draw conclusions and make future recommendations for improving the sales process. The results, corresponding findings, and future recommendations are presented in the following chapters.

4.4 Measures

The questionnaire contained 62 questions and statements. Appendix E provides an overview of the items, including their original items and references. The items were based on literature for validity and adapted to fit the research context. A 7-point Likert scale was used to measure all the constructs, ranging from strongly disagree (1) to strongly agree (7) unless indicated otherwise, which created a more detailed and comprehensive picture of the data.

Five MetrixLab employees tested the questions, statements, and instructions for clarity before the final version was distributed and necessary adjustments were made. For example, the items on AI readiness were based on the articles of Damejri and Salimi (2021) and Vize et al. (2013). These articles included AI readiness with 16 items in their questionnaires, each dimension comprising four items. When the questionnaire concept was tested among the five employees, they found some items of AI readiness unclear for their context. Furthermore, the questionnaire was too time-consuming. Based on the input of the employees, the decision was made to reduce the number of items for AI readiness to eight, each dimension consisting of two items, and keep the items most applicable to the sales context and MetrixLab. Another example of an adjustment is that the employees mentioned that they would answer differently depending on the solution for the statements related to perceived accuracy, attitude towards AI solutions, and behavioural intention. Therefore, it became clear that a distinction for these three constructs was needed based on the solutions, namely ACT Instant and Immerse. Thus, these statements were doubled and customised based on the intended solution, and each respondent filled in the whole questionnaire for both AI solutions (see Appendix E). The following section provides a clear overview of how each dimension was measured.

4.4.1 Dependent Variable – Behavioural Intention

Due to feedback from varying responses depending on the solution for statements of behavioural intention, the statements were duplicated and customised to each relevant solution, resulting in three items for ACT Instant and three for Immerse. The items were based on Venkatesh et al. (2003).

4.4.2 Independent Variables

As mentioned, eight items were formulated to investigate AI readiness. Each set, including two items, represents one distinctive dimension: optimism (AIR1, AIR2), inventiveness (AIR3, AIR4), discomfort (AIR5, AIR6), and insecurity (AIR7, AIR8) (Parasuraman, 2000; Parasuraman & Colby, 2015). Furthermore, three items were formulated to investigate a salesperson's awareness of the AI solution, originating from Flavián et al. (2022).

Similar to behavioural intention, the statements for perceived accuracy were duplicated and customised according to the relevant solution, resulting in three items for ACT Instant and three for Immerse. The Items were based on the literature from Shin (2021) and Chua et al. (2023). The items: PA3AI and PA3IM were measured on a different range of the 7-point Likert scale (far less accurate (1) to far more accurate (7)).

For analysing social influence, "subjective norm" and "social identity" focus on social interactions (Cheung & Lee, 2010). Therefore, SI1, SI2, and SI3 focussed on the "subjective norm" derived from Cao et al. (2021), and SI4, SI5 SI6 on "social identity" originating from Cheung and Lee (2010). Unlike all other items, SI4 was measured using Shamir and Kark's (2004) graphical approach (Figure 15 in Appendix F). Using a visual approach eliminated errors for this question, as words could not fully capture the respondents' perceptions (Liu et al., 2014). SI5 was measured on a different scale range (not at all (1) to very much (7)).

4.4.3 Mediating and Moderating Variables

Like behavioural intention and perceived accuracy, the statements for attitude were duplicated and tailored to each relevant solution, resulting in four items for ACT Instant and four for Immerse. The Items were based on the literature by Chua et al. (2023). Moreover, four items were adapted from the articles of Schepers et al. (2012) and Schepers et al. (2019) to assess customer stewardship.

4.4.4 Control Variables

In addition to these measures, the salesperson's characteristics were further defined and grouped on various control variables, like gender, age, nationality, geographical region, department, work experience and sales experience, which gained additional insights concerning the salesperson's characteristics. The descriptive statistics of the demographic variables are earlier presented in Table 2.

4.4.5 Exploratory Variables

Furthermore, exploratory variables based on literature were included in the questionnaire to investigate potential associations or uncover unexpected insights. Again, some additional quotes from the preliminary interviews are presented to illustrate the fit of these constructs with the research context.

4.4.5.1 Relative Advantage

Three items were developed to investigate relative advantage from To and Ngai (2006). The Diffusion of Innovation theory of Rogers (2010) defined "relative advantage" as the level to which an innovation or technology is indicated as better than the idea, program, or product it replaces. Since, in the solution selling context, a salesperson must assess the best-perceived solution that would fulfil customer needs and preferences and enhance their performance, the relative advantage could play a significant role. The following quote implies this:

> *"Whenever I do any of my new contacts, I sell the solution to make sure I give them the validation without a full test. With ACT Instant, they have tested at least something, rather than not testing at all. So, they know that the commercial can be used as an asset." (Salesperson 3)*

4.4.5.2 Customer Knowledge

Three items were formulated to assess customer knowledge, derived from Böhm et al. (2020). Because salespeople must understand customers' businesses, identify opportunities, and create solutions that meet customer needs (Böhm et al., 2020), customer knowledge could be a strong driver for selling solutions. Furthermore, interviewees mentioned the importance of knowing the customer and acting on their preferences. The following quotes illustrate interviewees not presenting an AI solution as this is not suitable for their customers:

> *"[...] among my customers, it's not really relevant. Yes, if you have COMPANY as a customer, I would probably present an ACT Instant sooner." (Salesperson 2)*

> *"I think many customers are still hesitant, but maybe we assume that without asking the customer, you feel that customers are looking for the hows and why's from open answers." (Salesperson 4)*

4.4.5.3 Selling Target

Unlike all other items, the three items describing the selling target were based on the findings of the unstructured exploratory interviews and compiled in consultation with MetrixLab supervisors due to their context dependency. Interviewees mentioned the low margin of selling AI solutions various times. The following quote illustrates the inferior margin of selling an AI solution, making it not attractive to present:

> *"And I also think, commercially, it might not be appealing to us if you look at the value of such an ACT Instant. Those AI solutions are often very cheap projects, where the customer does not receive much information either. So, I suppose, commercially, we are*

better off selling a slightly more expensive pre-test because there is more revenue for ourselves in there." (Salesperson 1)

4.4.5.4 Intrinsic Motivation

As mentioned, solution selling necessitates a different type of salesperson as they need several skills, attitudes, and behaviours to facilitate selling solutions (Salonen et al., 2021). Regarding attitudes, solution sellers benefit from intrinsic motivation (Ulaga & Loveland, 2014). Therefore, intrinsic motivation could be a strong driver for selling solutions, and three items were formulated, originating from Mallin and Pullins (2009).

4.5 Reliability and Validity

A Factor Analysis (FA) was conducted to create scale variables for the questionnaire items. Appendix G presents the details of this factor analysis for all the constructs. Four items were deleted for AI readiness after systematically evaluating the communalities and factor loadings (see Appendix G). Table 3 shows the constructs, including the corresponding items after the FA. The FA process revealed that the items split into ACT Instant and Immerse could not be combined into second-order constructs (see Appendix G). Hence, behavioural intention, attitude, and perceived accuracy remained disaggregated and were analysed separately on both solutions.

The following section will elaborate on the various strategies and methodologies employed to guarantee the accuracy and consistency of research outcomes while assessing the reliability and validity of quantitative research.

Item reliability. The dataset was indicated as suitable for an FA (see Appendix G) since Bartlett's test of Sphericity yielded a significant result, and all eigenvalues exceeded 1 (Field, 2009). Moreover, the KMO measures of sampling adequacy surpassed .70, indicating that a substantial amount of common variance existed among the variables and that the variables shared enough commonality to justify extracting factors and interpreting the results (Field, 2009). Additionally, as this study had a sample size of 104 respondents, a threshold value for a factor loading of .55 was guaranteed for including the item into a factor (see Appendix G) (Hair et al., 2010).

Internal consistency reliability. The values of AI readiness, social identity, selling target, and intrinsic motivation ranged between .60 and .80, below the desired Cronbach's alpha threshold of .80 (Field, 2009). Therefore, composite reliability (CR) was also calculated in this research, as Cronbach's alpha tends to underestimate internal reliability. Table 3 reveals that all values exceeded the CR cut-off point of .70, suggesting adequate internal consistency reliability (Nunnally & Bernstein, 1991).

Content and face validity. Before the questionnaire was conducted, it was tested on flow, length, completeness, and comprehensiveness among five employees outside the sample population. These employees were randomly selected outside of the sample to prevent people in the sample from knowing what to suspect when receiving the questionnaire, which minimised the possibility of response bias.

Construct validity. The Average Variance Extracted (AVE) value was estimated for convergent validity (Fornell & Larcker, 1981). A construct with an AVE value exceeding .50 suggests it accounts for more than half of the variance in the associated items (Hair et al., 2010). Table 3 shows that all values surpassed the AVE value of .50, implying convergent validity across the constructs.

Table 3 - Constructs, items, Cronbach's alpha, Composite Reliability, and the Average Variance Extracted

Constructs	Items	CA[a]	CR[b]	AVE[c]
1. Behavioural intention ACT Instant	BI1AI, BI2AI, and BI3AI	.85	.83	.61
2. Behavioural intention Immerse	BI1IM, BI2IM, and BI3IM	.84	.79	.56
3. Attitude towards ACT Instant	ATT1AI, ATT2AI, ATT3AI and ATT4AI	.90	.85	.60
4. Attitude towards Immerse	ATT1IM, ATT2IM, ATT3IM, and ATT4IM	.92	.88	.65
5. AI readiness	AIR3, AIR4, AIR5, and AIR6	.78	.84	.58
6. Awareness	AW1, AW2, and AW3	.94	.93	.85
7. Perceived accuracy ACT Instant	PA1AI, PA2AI, and PA3AI	.82	.84	.63
8. Perceived accuracy Immerse	PA1IM, PA2IM, and PA3IM	.84	.83	.62
9. Subjective norm	SI1, SI2, and SI3	.86	.89	.74
10. Social identity	SI4, SI5, and SI6	.67	.80	.57
11. Customer stewardship	CS1, CS2, CS3, and CS4	.85	.90	.69
12. Relative advantage	RA1, RA2, and RA3	.84	.91	.76
13. Customer knowledge	CK1, CK2, and CK3	.84	.88	.71
14. Selling target	ST1, ST2, and ST3	.60	.78	.54
15. Intrinsic motivation	IM1, IM2, and IM3	.72	.77	.54

Notes: behavioural intention, attitude, and perceived accuracy are disaggregated
[a] CA = Cronbach's Alpha.
[b] CR = Composite Reliability.
[c] AVE = Average Variance Extracted

4.6 Descriptive Statistics

Table 4 demonstrates the descriptive statistics for the dependent, independent, moderating, mediating, control and exploratory variables, including the mean or mode (when applicable), standard deviation, minimum, maximum, skewness, and kurtosis.

Table 4 - Descriptive statistics

	Mean	Mode	SD	Minimum	Maximum	$Z_{skewness}$	$Z_{kurtosis}$
1. Behavioural intention AI [a]	4.74		1.26	2.00	7.00	-.48	-1.01
2. Behavioural intention IM [b]	5.74		1.13	2.00	7.00	-3.57	.60
3. Attitude towards AI [a]	5.61		1.01	2.75	7.00	-3.83	1.60
4. Attitude towards IM [b]	6.44		.77	3.25	7.00	-6.99	6.43
5. AI readiness	4.74		1.14	2.00	6.75	-2.37	-1.03
6. Awareness	4.52		1.62	1.00	7.00	-1.78	-1.38
7. Perceived accuracy AI [a]	4.39		.94	1.67	7.00	-2.00	2.20
8. Perceived accuracy IM [b]	5.39		.90	2.67	7.00	-2.87	1.05
9. Subjective norm	5.70		.86	2.00	7.00	-5.33	5.99
10. Social identity	5.48		.76	3.00	6.67	-4.24	2.17
11. Customer stewardship	6.13		.87	2.50	7.00	-7.00	7.00
12. Relative advantage	5.64		1.18	1.00	7.00	-5.83	6.63
13. Customer knowledge	5.67		.84	3.33	7.00	-3.60	1.85
14. Selling target	3.60		1.18	1.00	6.67	-.21	.02
15. Intrinsic motivation	5.21		1.00	3.00	7.00	-.92	-1.69
Gender		0	.50	0	1	1.51	-4.07
Age	42.20		9.30	27	68	1.84	-.85
Nationality		2	.69	1	3	-.16	-1.83
Geographical region		2	1.11	1	4	1.90	-2.52
Department		1	.87	1	3	3.55	-2.48
Involvement AI [a]		1	1.51	1	5	1.63	-2.74
Involvement IM [b]		5	1.53	1	5	-2.53	-2.61
Work experience		5	.98	1	5	-6.15	2.26
Sales experience		1	1.38	1	5	4.12	-.79

Notes:

[a] AI = ACT Instant.

[b] IM = Immerse.

4.7 Data Analysis

4.7.1 Examination of the Data

The dataset was thoroughly examined for missing values and outliers before the analysis to prevent potential biases but tried to avoid case deletion due to the small sample size (N= 104) (Hair et al., 2010). After no missing values were found by examining the data, both univariate and multivariate outliers in the dataset were checked. As the questionnaire environment limited respondents in answering, the possibility for univariate outliers occurring was excluded. To identify multivariate outliers, the Mahalanobis Distance was calculated in SPSS, which measures the distance of each observation in multidimensional space from the mean centre of all observations (Hair et al., 2010). The results indicated no multivariate outliers following the cut-off point Hair et al. (2010) suggested of .001.

4.7.2 Overcoming Biases

Several measures were implemented to mitigate potential response biases and repetitive answering. Two biases were considered primarily: the common method-, and the non-response bias. The common method bias could occur since the respondents controlled the dependent and independent variables. Podsakoff et al. (2003) defined the common method bias as the variance attributable to the measurement procedure rather than the constructs the measures represent.

Adding reversed items to the questionnaire disrupted the response pattern, helping overcome the common method bias. Moreover, multiple question types provided by the MetrixLab questionnaire environment were mixed along the questionnaire to reduce the flow of potential response patterns (see Appendix F) (Liu et al., 2014). However, the common method bias could still exist despite thoroughly considering nearly all procedural remedies. Therefore, the dataset was tested using Harman's single-factor score. This test included loading all items into one common factor and investigating the total variance. The total variance was 26.20%, which concluded that common method bias does not affect the data as it was less than 50% (Podsakoff et al., 2003).

Additionally, the non-response bias was considered. The results could not be generalised if questionnaire respondents' answers substantially differed from the potential answers of non-respondents (Podsakoff et al., 2003). Even though analysing non-respondents' answers is impossible, comparing late to early respondents is an alternative procedure (Armstrong & Overton, 1977). Two significant effects emerged (see Appendix H). Respondents who participated before the reminder rated their subjective norm ($t(63.46) = -1.69$, $p < .01$) and their attitude towards Immerse ($t(63.42) = -.58$, $p < .01$) significantly lower than that of late respondents.

4.7.3 Correlations

The constructs' correlations were examined and presented in Table 5 following the reliability and validity assessment. Despite the low sample size, strong correlations were observed among the variables with a statistical significance at $p < .01$. Notably, attitude and behavioural intention in both cases: ACT Instant and Immerse, reached high correlation values above .70 (see Table 5). These high correlations were not surprising since the factor analysis showed high cross-loadings between attitude and behavioural intention in both cases (see Tables 13 and 14 in Appendix G).

Table 5 - Correlations matrix

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Behavioural intention AI [a]														
2. Behavioural intention IM [b]	.41**													
3. Attitude towards AI [a]	.72**	.29**												
4. Attitude towards IM [b]	.29**	.71**	.40**											
5. AI readiness	.34**	.18	.32**	.13										
6. Awareness	.24*	.38**	.23*	.46**	.25*									
7. Perceived accuracy AI [a]	.47**	-.02	.59**	.22*	.19	-.04								
8. Perceived accuracy IM [b]	.20*	.52**	.25*	.67**	.10	.29**	.15							
9. Subjective norm	.35**	.28**	.50**	36**	.26**	.21*	.22*	.28**						
10. Social identity	.34**	.14	.40**	.20*	.03	.12	.41**	.19*	.28**					
11. Customer stewardship	.32**	.38**	.36**	.42**	.19	.19	.09	.34**	.24*	.21*				
12. Relative advantage	.29**	.34**	.40**	.40**	.33**	.36**	.23*	.22*	.64**	.19	.28**			
13. Customer knowledge	.48**	.43**	.37**	.50**	.21*	.43**	.16	.33**	.31**	.23*	.50**	.31**		
14. Selling target	.06	.01	-.08	-.06	-.05	-.12	.02	-.15	-.03	.01	-.02	-.04	.04	
15. Intrinsic motivation	.31**	.42**	.28**	.48**	.08	.37**	.15	.32**	.29**	.19	.41**	.44**	.43**	.03

Notes: * indicates $p < .05$, ** indicates $p < .01$, *** indicates $p < .001$.
[a] AI = ACT Instant.
[b] IM = Immerse.

4.7.4 Assumptions

Two correlation coefficients reached medium to high values (> .70) (see Table 5). However, no correlation coefficients exceeded .80, which suggests the presence of multicollinearity. Hence, Variance Inflation Factors (VIF) were analysed. The VIF values ranged from 1.12 to 1.58, which was below the threshold of 10.00 (Field, 2009). However, the average VIF values were above 1.00, indicating the potential for multicollinearity. Consequently, tolerance values were examined. All tolerance values were above .20, showing no evidence of multicollinearity (Field, 2009).

Socially desirable responses could occur since the questionnaire emphasised respondents' opinions within their current employer's context. Besides, a normality check was needed due to the relatively small sample size (N= 104) and skewness that could still affect the analysis (Vinzi et al., 2010). According to Hair et al. (2010) and Byrne (2010), if the values for skewness are between -2 and +2 and the values for kurtosis are between -7 to +7, the data is considered normal. The results of Table 4 indicate that most items violate the skewness criterion, including negative skewness. However, they do not violate the kurtosis criterion. Attempts to transform the items, including squared or log transformations, revealed a similar pattern. Therefore, the data were not converted.

5. Results

As mentioned, a questionnaire invitation was sent to 198 MetrixLab employees, and 104 (52.53%) completed the questionnaire. The results of these responses are presented in this chapter. First, the conceptual model is estimated, including the control variables for ACT Instant and Immerse. Afterwards, further analysis was done to evaluate the exploratory variables. The analyses and hypothesis testing were conducted in SPSS Statistics using the PROCESS Macro. This modelling tool facilitates the implementation of mediation, moderation, and conditional process analysis with observed variables (Hayes et al., 2017). Furthermore, PROCESS estimates direct and indirect effects in models with one or more mediators (parallel and serial), two- and three-way interactions in moderation models, and conditional indirect effects in models of moderated mediation with one or more mediators or moderators (Hayes et al., 2017). Therefore, the hypotheses were tested with PROCESS, as the conceptual model contained a mediator and moderator with multiple interactions.

5.1 PROCESS Models

First, the core model without moderation effects was estimated using PROCESS Template 4 following the direct paths in the proposed conceptual model. After that, the hypothesised moderation effects are examined. Unfortunately, PROCESS allows only one independent variable (X); the other variables must be included as covariates. Hence, only the moderation interactions on the relationships between the independent variable (X), mediator (M) and the dependent variable (Y) can be tested. The interaction effect of the included covariates and the moderator cannot be tested simultaneously. However, the proposed conceptual model contained multiple interaction effects. Therefore, the hypothesised mediation effects must be separated and repeated three times, varying from the independent variable (X) between subjective norm, social identity, and perceived accuracy. In each analysis, the other independent variables and all the control variables that are objectively measured were included as covariates. Appendix I provides an overview of the various combinations to test the conceptual model, including the corresponding templates. Model 1 presents the core model's results without interaction effects, used to conclude the direct effects hypotheses (H1 to H6). Models 2, 3 and 4 are used to investigate the moderating effects of customer stewardship (H7 to H9).

5.2 Regression Analyses ACT Instant

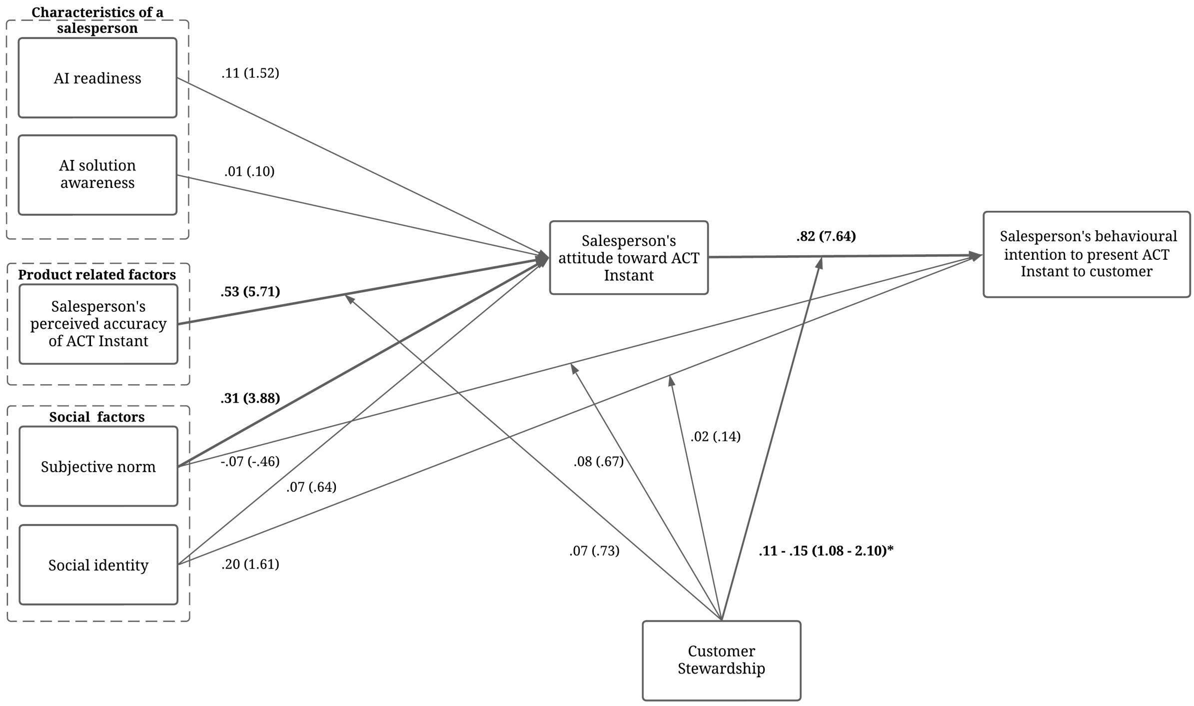
Table 6 reports the results of the regression analyses, including the path coefficients for the models' estimates for ACT Instant. Furthermore, the strengths and directions between the relationships, excluding the control variables, are illustrated in Figure 4, where bold arrows indicate the significant relationships. The following sections will provide the significant direct and moderating effects of ACT Instant, including the (not) supported hypotheses.

Table 6 - Regression analyses results for ACT Instant

	Study 1: ACT Instant															
	Model 1 No interaction model				Model 2 Perceived accuracy				Model 3 Subjective norm				Model 4 Social identity			
	Dependent variable				Dependent variable				Dependent variable				Dependent variable			
	Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]	
	B	t	B	t	B	t	B	t	B	t	B	t	B	t	B	t
Constant	.54	.68	-.42	-.46	**-2.53**	**-2.95**	**4.17**	**4.07**	**-3.06**	**-3.83**	**3.71**	**4.29**	**-4.70**	**-6.19**	**4.97**	**5.61**
Direct effects																
AI readiness	.11	1.52			.08	1.21			.11	1.52			.11	1.52		
Awareness	.01	.10			-.00	-.01			.01	.10			.01	.10		
Perceived accuracy ACT Instant	**.53**	**5.71**			**.53**	**5.89**	.03	.20	**.53**	**5.71**			**.53**	**5.71**		
Subjective norm	**.31**	**3.88**	-.07	-.46	**.33**	**3.63**	-.06	-.54	**.31**	**3.88**	-.08	-.72	**.31**	**3.88**	-.07	-.59
Social identity	.07	.64	.20	1.61	.03	.31	.14	1.13	.07	.64	.15	1.19	.07	1.07	.15	1.23
Attitude towards ACT Instant			**.82**	**7.64**			**.82**	**6.27**			**.83**	**7.74**			**.83**	**7.65**
Customer stewardship					**.22**	**2.48**	.21	1.68			.24	1.78			.21	1.68
Moderating effects																
Perceived accuracy AI [a] * Customer stewardship					.07	.73										
Subjective norm * Customer stewardship											.08	.67				
Social identity * Customer stewardship															.02	.14
Attitude ACT Instant * Customer stewardship							**.15**	**2.10**			.11	1.08			**.15**	**2.03**
Control variable paths																
Gender: Female [b]	.17	1.07	-.23	-1.31	.18	1.18	-.23	-1.37	.17	1.07	-.25	-1.36	.17	1.07	-.25	-1.37
Age	**-.03**	**-2.21**	.00	-.01	**-.02**	**-2.05**	-.00	-.09	**-.03**	**-2.21**	.00	-.59	**-.03**	**-2.21**	.00	-.04
Nationality: Asian Pacific [c]	-.43	-1.49	.35	1.06	-.40	-1.42	.35	1.04	-.43	-1.49	.35	1.10	-.43	-1.49	.37	1.14
Nationality: American [c]	.11	.32	-.16	-.41	.04	.13	-.26	-.67	.11	.32	-.23	-.59	.11	.32	-.25	-.64
Geographical region: AMEA [d]	.39	1.26	**-.81**	**-2.34**	.36	1.20	**-.78**	**-2.16**	.39	1.26	**-.79**	**-2.30**	.39	1.26	**-.79**	**-2.27**
Geographical region: LATAM [d]	-.30	-.65	**1.35**	**2.42**	-.23	-.50	**1.36**	**2.63**	-.30	-.65	**1.32**	**2.56**	-.30	-.65	**1.35**	**2.63**
Geographical region: NA [d]	.12	.34	.22	.55	.11	.33	.24	.61	.12	.34	.20	.51	.12	.34	.24	.61
Department: GTIC [e]	-.11	-.40	.06	.18	.05	.19	.22	.67	-.11	-.40	.23	.70	-.11	-.40	.23	.68
Department: Research [e]	-.25	-1.13	-.12	-.47	-.08	-.35	-.03	-.11	-.25	-1.13	-.01	-.02	-.25	-1.13	-.04	-.13
Involvement ACT Instant	.08	1.21	**.19**	**2.75**	.09	1.47	**.20**	**2.92**	.08	1.21	**.21**	**2.95**	.08	1.21	**.20**	**2.92**
Work experience	.08	.79	-.04	-.32	.10	1.02	.00	.00	.08	.79	.01	.05	.08	.79	-.00	-.03
Sales experience	.13	1.80	-.14	-1.69	.13	1.82	-.14	-1.61	.13	1.80	-.15	-1.75	.13	1.80	-.14	-1.67
Variance explained (R^2)	60.6%		63.9%		63.4%		65.9%		60.6%		66.1%		60.6%		65.9%	

Notes:
Bold values are significant at the $p < .05$ level.
[a] AI = ACT Instant.
[b] Dummy variable: Male coded as 0, female coded as 1.
[c] Dummy variable: European coded as 0, Asian Pacific or American coded as 1.
[d] Dummy variable: Europe coded as 0, AMEA, LATAM or NA coded as 1.
[e] Dummy variable: Sales coded as 0, GTIC or Research coded as 1.

Figure 4 - Model results for testing hypotheses ACT Instant



Notes:
Bold arrows indicate the significant relationships at the $p < .05$ level.
* indicates β-values ranging from .11 to .15 and t-values ranging from 1.08 and 2.10. See Table 6 for specific values in the different models.

5.2.1 Direct Effects

Model 1 showed that the effect of attitude towards ACT Instant on behavioural intention to present ACT Instant was positive and significant (β = .82, t = 7.64), which is in line with H1 and hence supported. No significant effects were found for AI readiness (β = .11, t = 1.52) and awareness (β = .01, t = .10) on attitude towards ACT Instant, which indicates that H2 and H3 are not supported.

Moreover, this model showed significant positive direct effects of perceived accuracy of ACT Instant (β = .53, t = 5.71) and subjective norm (β = .31, t = 3.88) on attitude towards ACT Instant. The positive and significant effect of the perceived accuracy of ACT Instant on attitude towards ACT Instant provides support for H4. However, H5 is only partially supported. While subjective norm significantly affected the attitude towards ACT Instant (β = .31, t = 3.88), social identity did not significantly affect the attitude towards ACT Instant (β = .07, t = .64). Furthermore, no significant effects were found for subjective norm (β = -.07, t = -.46) and social identity (β = .20, t = 1.61) on behavioural intention to present ACT Instant, which indicates that H6 is not supported.

5.2.2 Indirect Effects

Additional significance tests of the (unconditional) indirect effects of perceived accuracy and subjective norm on behavioural intention ACT Instant, mediated by attitude towards ACT Instant, were performed. Table 7 shows that only perceived accuracy has a significant total effect, which implies that only this relationship: perceived accuracy → attitude → behavioural intention, could be classified as a mediation effect, and subjective norm as an indirect effect (Mathieu & Taylor, 2006). Still, other studies have argued that the mediation effect is appropriate when the X → M and M → Y paths are significant and have loosened the precondition of the total significant effect (Kenny et al., 1998; MacKinnon et al., 2002).

Table 7 - Total-, direct-, and indirect effects on behavioural intention ACT Instant

	Behavioural intention ACT Instant											
	Total effect [a]				Direct effect [b]				Indirect effect [c]			
	B	t	LLCI	ULCI	B	t	LLCI	ULCI	B	SE	LLCI	ULCI
Perceived accuracy	**.44**	**3.42**	**.19**	**.70**	.04	.29	-.22	.29	**.41**	**.10**	**.21**	**.61**
Subjective norm	.18	1.41	-.07	.43	-.09	-.79	-.32	.14	**.27**	**.08**	**.12**	**.45**

Notes:
Significant values in bold; t-values for indirect effects are not reported due to their low statistical power and Type I error rates.
[a] The total effect of X on Y
[b] The direct effect of X on Y.
[c] The mediating effect of X → M → Y, with mediator attitude towards ACT Instant.

The additional tests indicated that the indirect effect of perceived accuracy on behavioural intention was significant (CI95% = [.21; .61]), and the indirect effect of subjective norm on behavioural intention was significant (CI95% = [.12; .45]) (see Table 7). Besides, a full mediation effect was indicated since the direct effect of perceived accuracy and subjective norm on behavioural intention ACT Instant was insignificant (see Table 7). This demonstrates that attitude towards ACT Instant functions as a mediator for the relationship between perceived accuracy and behavioural intention and between subjective norm and behavioural intention.

5.2.2.1 The Interaction Effect between Perceived Accuracy and Customer Stewardship

Model 2 presents the moderating effects between the perceived accuracy of ACT Instant and customer stewardship (PAAI × CS) and between attitude towards ACT Instant and customer stewardship (ATTAI × CS) (see Table 6). These results showed that customer stewardship did not significantly moderate the relationship between the perceived accuracy of ACT Instant and attitude towards ACT Instant ($\beta = .07$, $t = .73$). Hence, H7 is not supported.

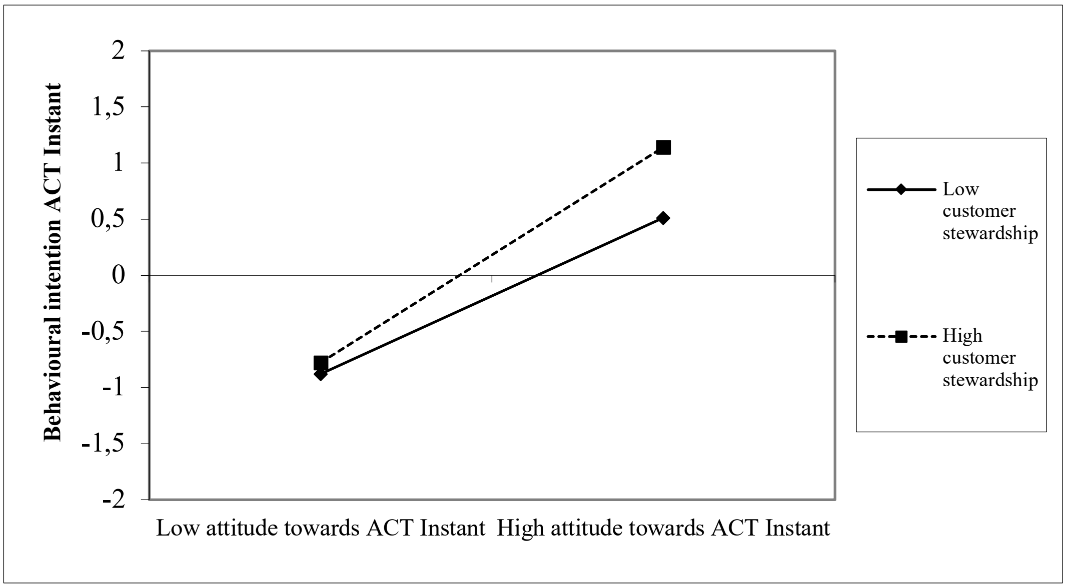
5.2.2.2 The Interaction Effect between Social Influence and Customer Stewardship

H8 was tested using two subconstructs: subjective norm and social identity, for social influence. Model 3 presents the moderating effects between used between subjective norm and customer stewardship (SN × CS) and between attitude towards ACT Instant and customer stewardship (ATTAI × CS) (see Table 6). These results showed that customer stewardship did not significantly moderate the relationship between subjective norm and behavioural intention to present ACT Instant ($\beta = .08$, $t = .67$). Furthermore, Model 4, showing the interaction effect between social identity and customer stewardship (SI × CS) and between attitude towards ACT Instant and customer stewardship (ATTAI × CS), showed that customer stewardship did not significantly moderate the relationship between and social identity and behavioural intention to present ACT Instant (β = .02, t = .14). Consequently, as the interaction effects of customer stewardship on the subjective norm and social identity are insignificant, there is no support for H8.

5.2.2.3 The Interaction Effect between Attitude Towards ACT Instant and Customer Stewardship

The interaction effect between attitude towards ACT Instant and customer stewardship (ATTAI × CS) was included in Models 2, 3 and 4. Model 2 showed that customer stewardship positively moderated the relationship between attitude towards ACT Instant and behavioural intention to present ACT Instant (β =.15, t = 2.10) (see Table 6). Besides, Model 4 also showed the positive moderation of customer stewardship on this positive relationship (β = .15, t = 2.03). This significant moderation means that when a salesperson perceives a high level of customer stewardship, it strengthens the positive relationship between a salesperson's attitude toward ACT Instant and their behavioural intention to present it to the customer compared to a salesperson with a low level of customer stewardship (see Figure 5).

Figure 5 - The interaction effect of attitude towards ACT Instant and customer stewardship



However, Model 3 showed that customer stewardship did not moderate the relationship between attitude towards ACT Instant and behavioural intention to present ACT Instant (β = .11, t = 1.08) (see Table 6). The discrepancies between the three models indicate that the interaction effect between a salesperson's attitude towards ACT Instant and customer stewardship (ATTAI × CS) depends on the preceding relationships. The significant relationship between subjective norm and attitude towards ACT Instant and the interaction effect between subjective norm and customer stewardship (SN × CS) might cause the missing significance. As H9 stated, a negative moderation of customer stewardship on the positive relationship between attitude towards an AI solution and behavioural intention, the results are in the opposite direction and therefore do not support the proposed hypothesis.

5.2.3 Control Variables Effects

Including measurable demographic variables as control variables in the regression analyses helped to control for possible influences on a salesperson's attitude towards ACT Instant and their behavioural intention to present it. Model 1 showed that a salesperson's age significantly negatively affects their attitude towards ACT Instant ($\beta = -.03$, $t = -2.21$) and a marginally significant and positive effect for sales experience on attitude towards ACT Instant ($\beta = .13$, $t = 1.80$) (see Table 6). Besides, the results of the control variables in Model 1 showed multiple effects for behavioural intention to present ACT Instant. Geographical region significantly affects behavioural intention to present ACT Instant for AMEA and LATAM. The behavioural intention to present ACT Instant is significantly lower for salespeople who work in Asia, the Middle East and Africa compared to Europe ($\beta = -.81$, $t = -2.34$) and significantly higher for salespeople working in Latin America compared to Europe ($\beta = 1.35$, $t = 2.42$) (see Table 6). Moreover, the number of times a salesperson is involved in the selling process of ACT Instant significantly affects behavioural intention to present ACT Instant. A salesperson's involvement in ACT Instant positively and significantly affected their intention to present it ($\beta = .19$, $t = 2.75$).

5.3 Regression Analyses Immerse

Table 8 reports the results of the regression analyses, including the path coefficients for the estimates of the models of Immerse. Furthermore, the strengths and directions between the relationships, excluding the control variables, are illustrated in Figure 6, where bold arrows indicate the significant relationships. The following sections will provide the significant direct and moderating effects in the case of Immerse, including the (not) supported hypotheses.

Table 8 - Regression analyses results for Immerse (IM)

	Study 2: Immerse															
	Model 1 No interaction model				Model 2 Perceived accuracy				Model 3 Subjective norm				Model 4 Social identity			
	Dependent variable				Dependent variable				Dependent variable				Dependent variable			
	Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]	
	B	t	B	t	B	t	B	t	B	t	B	t	B	t	B	t
Constant	**2.58**	**3.87**	-.13	-.12	**-1.41**	**-2.38**	**5.29**	**5.32**	**-3.04**	**-4.33**	**5.65**	**6.27**	**-3.85**	**-6.06**	**5.20**	**5.63**
Direct effects																
AI readiness	-.05	-.98			-.09	-1.83			-.05	-.98			-.05	-.98		
Awareness	**.11**	**2.55**			**.11**	**2.81**			**.11**	**2.55**			**.11**	**2.55**		
Perceived accuracy Immerse	**.41**	**6.08**			**.36**	**5.47**	.06	.49	**.41**	**6.08**			**.41**	**6.08**		
Subjective norm	**.15**	**2.07**	.08	.70	.12	1.86	.06	.56	**.15**	**2.07**	.07	.60	**.15**	**2.07**	.06	.58
Social identity	.00	.04	.00	.04	-.03	-.37	-.02	-.17	.00	.04	-.01	-.10	.00	.04	-.02	-.13
Attitude towards Immerse			**.84**	**6.30**			**.74**	**4.29**			**.79**	**5.23**			**.78**	**5.25**
Customer stewardship					.08	1.02	.16	1.31			.15	1.14			.16	1.31
Moderating effects																
Perceived accuracy IM [a] * Customer stewardship					**-.17**	**-2.52**										
Subjective norm * Customer stewardship											-.02	-.15				
Social identity * Customer stewardship															.01	.04
Attitude Immerse * Customer stewardship							.01	.12			.02	.15			.01	.09
Control variable paths																
Gender: Female [b]	.21	1.71	.15	.82	**.26**	**2.28**	.18	.95	.21	1.71	.18	.94	.21	1.71	.18	.94
Age	.00	.02	-.00	-.09	.00	.46	.00	.06	.00	.02	.00	.00	.00	.02	.00	.02
Nationality: Asian Pacific [c]	-.11	-.53	.17	.51	-.04	-.20	.17	.52	-.11	-.53	.17	.52	-.11	-.53	.17	.51
Nationality: American [c]	-.40	-1.53	-.30	-.75	-.43	-1.73	-.37	-.91	-.40	-1.53	-.36	-.89	-.40	-1.53	-.36	-.87
Geographical region: AMEA [d]	-.10	-.43	-.16	-.44	-.21	-.95	-.19	-.53	-.10	-.43	-.18	-.50	-.10	-.43	-.17	-.48
Geographical region: LATAM [d]	.44	1.25	.64	1.23	.48	1.44	.69	1.31	.44	1.25	.72	1.35	.44	1.25	.71	1.34
Geographical region: NA [d]	.42	1.60	.13	.32	.34	1.36	.15	.36	.42	1.60	.15	.37	.42	1.60	.14	.34
Department: GTIC [e]	.08	.37	.14	.43	.14	.70	.24	.73	.08	.37	.22	.67	.08	.37	.23	.68
Department: Research [e]	-.07	-.37	-.27	-1.03	.10	.59	-.16	-.59	-.07	-.37	-.18	-.66	-.07	-.37	-.18	-.65
Involvement Immerse	**.13**	**2.44**	.13	1.61	**.14**	**2.79**	.15	1.76	**.13**	**2.44**	.15	1.75	**.13**	**2.44**	.15	-1.74
Work experience	.02	.20	-.07	-.59	.04	.50	-.06	.48	.02	.20	-.06	-.51	.02	.20	-.06	-.49
Sales experience	-.03	-.60	-.06	-.71	-.04	-.79	-.06	-.73	-.03	-.60	-.06	-.72	-.03	-.60	-.06	-.71
Variance explained (R^2)	61.2%		55.8%		67.0%		56.9%		61.2%		56.8%		61.2%		56.8%	

Notes:

Bold values are significant at the $p < .05$ level.

[a] IM = Immerse.

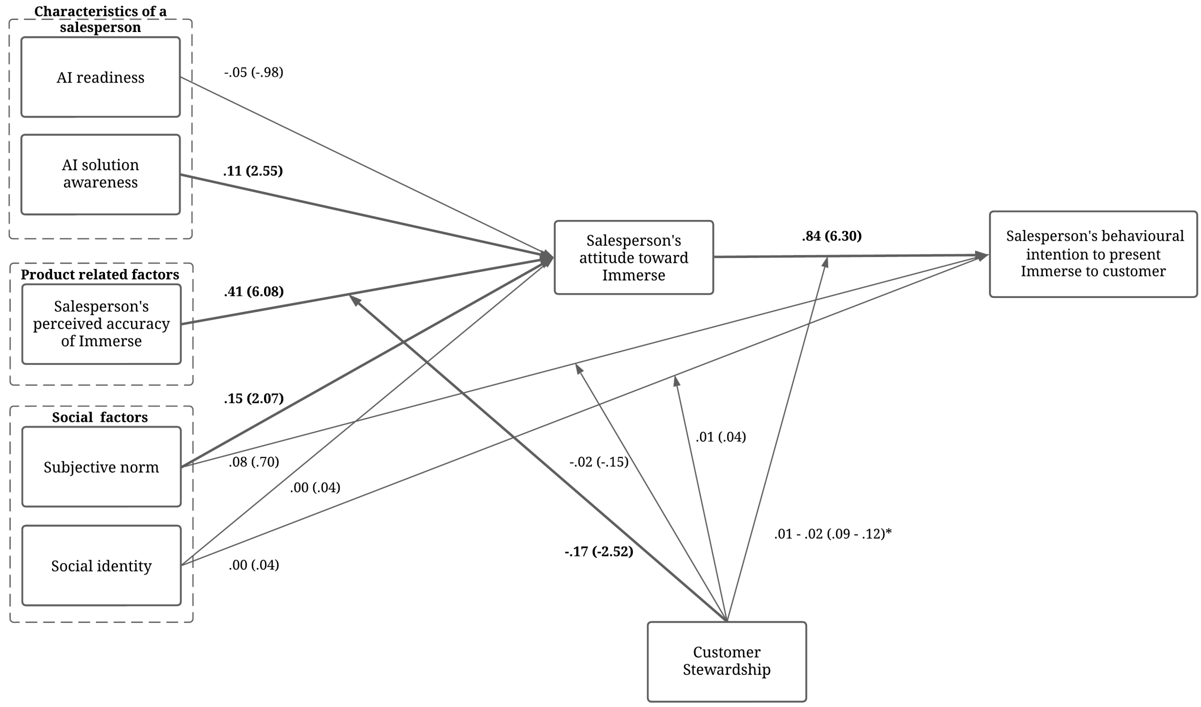
[b] Dummy variable: Male coded as 0, female coded as 1.

[c] Dummy variable: European coded as 0, Asian Pacific or American coded as 1.

[d] Dummy variable: Europe coded as 0, AMEA, LATAM or NA coded as 1.

[e] Dummy variable: Sales coded as 0, GTIC or Research coded as 1.

Figure 6 - Model results for testing hypotheses Immerse



Notes:
Bold arrows indicate the significant relationships at the $p < .05$ level.
* indicates β values ranging from .01 to .02 and t values ranging from .09 and .12. See Table 8 for specific values in the different models.

5.3.1 Direct Effects

Model 1 (see Table 8) showed that the effect of attitude towards Immerse on behavioural intention to present Immerse was positive and significant (β = .84, t = 6.30), which is in line with H1 and hence supported. No significant direct effect of AI readiness on attitude towards Immerse was found (β = -.05, t = -.98), which indicates that H2 is not supported. Besides, this model showed significant positive direct effects of awareness (β = .11, t = 2.55) and perceived accuracy of Immerse (β = .41, t = 6.08) on attitude towards Immerse (see Table 8). This provides support for H3 and H4. Furthermore, while subjective norm significantly affected the attitude towards Immerse (β = .15, t = 2.07), social identity did not significantly affect the attitude towards Immerse (β = .00, t = .04). Therefore, H5 is partially supported. No significant effects were found for subjective norm (β = .08, t = .70) and social identity (β = .00, t = .04) on behavioural intention to present Immerse, which indicates that H6 is not supported (see Table 8).

5.3.2 Indirect Effects

Additional significance tests of the (unconditional) indirect effects of awareness, perceived accuracy and subjective norm on behavioural intention Immerse, mediated by attitude towards Immerse, were performed. Table 9 shows that only perceived accuracy has a significant total effect, which implies that only this relationship: perceived accuracy → attitude → behavioural intention, could be classified as a mediation effect, and awareness and subjective norm as an indirect effect (Mathieu & Taylor, 2006).

However, like for ACT Instant, the precondition of the total significant effect was loosened (Kenny et al., 1998; MacKinnon et al., 2002).

Table 9 - Total-, direct-, and indirect effects on behavioural intention Immerse

	Behavioural intention Immerse											
	Total effect [a]				Direct effect [b]				Indirect effect [c]			
	B	t	LLCI	ULCI	B	t	LLCI	ULCI	B	SE	LLCI	ULCI
Awareness	.11	1.52	-.03	.26	.03	.39	-.11	.16	**.09**	**.04**	**.01**	**.18**
Perceived accuracy	**.39**	**3.31**	**.16**	**.63**	.07	.52	-.19	.32	**.33**	**.09**	**.16**	**.51**
Subjective norm	.16	1.33	-.08	.42	.05	.43	-.18	.27	**.11**	**.06**	**.01**	**.24**

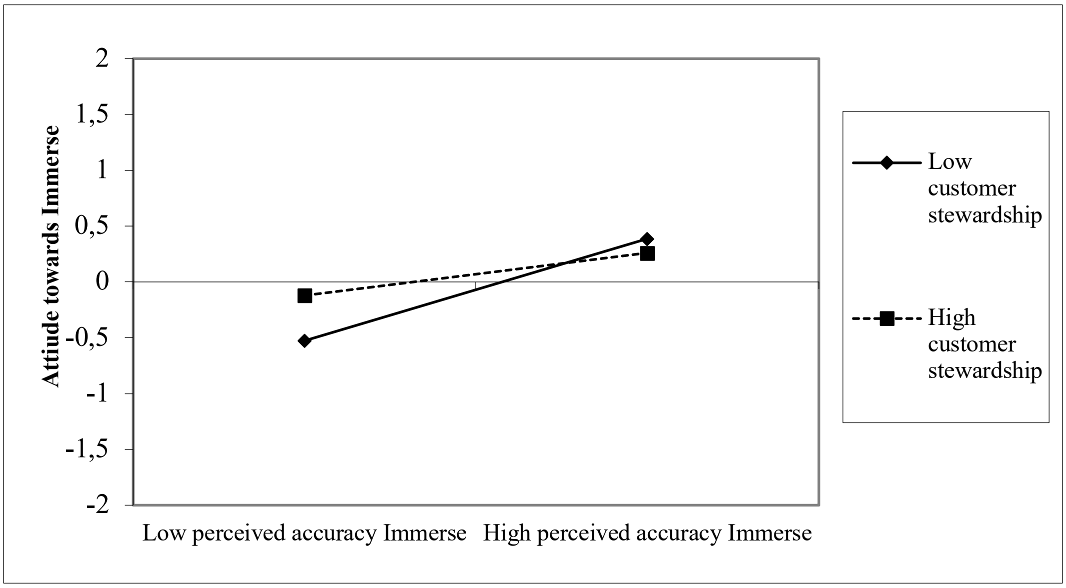
Notes:
Significant values in bold; t-values for indirect effects are not reported due to their low statistical power and Type I error rates.
[a] The total effect of X on Y
[b] The direct effect of X on Y.
[c] The Mediating effect of X → M → Y, with mediator attitude towards Immerse.

The additional tests indicated that the indirect effect of awareness on behavioural intention Immerse was significant (CI95% = [.01; .18]), the indirect effect of perceived accuracy Immerse on behavioural intention was significant (CI95% = [.16; .51]), and the indirect effect of subjective norm on behavioural intention was significant (CI95% = [.01; .24]) (see Table 9). Besides, a full mediation effect was indicated since the direct effect of awareness, perceived accuracy and subjective norm on behavioural intention Immerse was insignificant (see Table 9). This suggests that attitude towards Immerse mediates the relationship between awareness and behavioural intention, perceived accuracy and intention, and subjective norm and intention.

5.3.2.1 The Interaction Effect between Perceived Accuracy and Customer Stewardship

Model 2 presents the moderating effects between the perceived accuracy of Immerse and customer stewardship (PAIM × CS) and between attitude towards Immerse and customer stewardship (ATTIM × CS) (see Table 8). These results showed that customer stewardship negatively and significantly moderated the relationship between the perceived accuracy of Immerse and attitude towards Immerse ($\beta = -.17$, $t = -2.52$). This significant moderation means that when a salesperson has a high level of customer stewardship, it weakens the positive relationship between a salesperson's perceived accuracy of Immerse and their attitude towards Immerse to present compared to a salesperson with a low level of customer stewardship (see Figure 7). Hence, H7 is not supported as the significant effects were in the opposite direction of the proposed hypothesis.

Figure 7 - Interaction effect of perceived accuracy of Immerse and customer stewardship



5.3.2.2 The Interaction Effect between Social Influence and Customer Stewardship

H8 was tested using two subconstructs: subjective norm and social identity, for social influence. Model 3 presents the moderating effects between used between subjective norm and customer stewardship (SN × CS) and between attitude towards Immerse and customer stewardship (ATTIM × CS), and Model 4 presents the moderating effect between used between social identity and customer stewardship (SI × CS) and between attitude towards Immerse and customer stewardship (ATTIM × CS) (see Table 8). Model 3 showed that customer stewardship did not moderate the relationship between subjective norm and behavioural intention to present Immerse (β = -.02, t = -.15). Moreover, Model 4 showed that customer stewardship did not moderately affect the relationship between social identity and behavioural intention to present Immerse (β = .01, t = .04). Consequently, as the interaction for subjective norm and social identity are insignificant, there is no support for H8.

5.3.2.3 The Interaction Effect between Attitude Towards Immerse and Customer Stewardship

Models 2, 3 and 4 include the interaction effect of customer stewardship on the relationship between attitude towards Immerse and behavioural intention (see Table 8). These models showed no significant moderation for customer stewardship on the relationship between a salesperson's attitude towards Immerse and their behavioural intention to present it (2: β = .01, t = .12; 3: β = .02, t = .15; 4: β = .01, t = .09). Therefore, H9 is not supported.

5.3.3 Control Variables Effects

Including measurable demographic variables as control variables in the regression analyses helped to control for possible influences on a salesperson's attitude towards Immerse and their behavioural intention to present it. Model 1 showed that the number of times a salesperson is involved in the selling process of Immerse positively and significantly affects their behavioural intention to present it ($\beta = .13$, $t = 2.44$) (see Table 8). However, the results of Model 1 showed no significant effects of control variables on behavioural intention. Model 2 showed a positive and significant effect for gender on the attitude towards Immerse ($\beta = .26$, $t = 2.28$). Compared to Model 2, the effect of gender on attitude towards Immerse was marginally significant in Model 1 ($\beta = .21$, $t = 1.71$) (see Table 8). Further analyses indicated that the interaction between perceived accuracy and customer stewardship (PAIM × CS) was the leading cause of this difference.

5.4 Summary Results

Table 10 shows the summary results for the hypotheses in the case of ACT Instant and Immerse, providing the similarities and differences.

Table 10 - Summary hypotheses testing ACT Instant and Immerse

	Hypotheses	ACT Instant	Immerse
Direct effects			
H1	Salesperson's attitude towards the AI solution positively affects their behavioural intention to present it to the customer.	Supported	Supported
H2	Salesperson's AI readiness positively affects their attitude towards the AI solution.	Not supported	Not supported
H3	Salesperson's awareness of the AI solution positively affects their attitude towards it.	Not supported	Supported
H4	Salesperson's perceived accuracy of the outcomes from the AI solution positively affects their attitude towards the AI solution.	Supported	Supported
H5	The social influence of peers positively affects a salesperson's attitude towards the AI solution	Partially supported	Partially supported
	Subjective norm	Supported	Supported
	Social identity	Not supported	Not supported
H6	The social influence of peers positively affects a salesperson's behavioural intention to present the AI solution to the customer.	Not supported	Not supported
	Subjective norm	Not supported	Not supported
	Social identity	Not supported	Not supported
Moderating effects			
H7	Customer stewardship moderates the positive relationship between a salesperson's perceived accuracy and their attitude towards the AI solution such that this relationship becomes stronger when a salesperson perceives a higher level of customer stewardship.	Not supported	Not supported [a]
H8	Customer stewardship moderates the positive relationship between the social influence of peers and a salesperson's behavioural intention to present the AI solution to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.	Not supported	Not supported
	Subjective norm * Customer stewardship	Not supported	Not supported
	Social identity * Customer stewardship	Not supported	Not supported
H9	Customer stewardship moderates the positive relationship between a salesperson's attitude towards the AI solution and their behavioural intention to present it to the customer such that this relationship becomes weaker when a salesperson perceives a high level of customer stewardship.	Not supported [a]	Not supported

Notes:
[a] Not supported, significant effect in the opposite direction of the proposed hypothesis.

5.5 Further Analysis

As mentioned, the exploratory constructs: relative advantage, customer knowledge, selling target, and intrinsic motivation were included in the questionnaire to investigate potential relationships or uncover unexpected insights. First, the direct effects were estimated using linear regression following the proposed conceptual model's direct paths and adding the exploratory constructs. The results showed that relative advantage significantly impacted attitude towards Immerse ($\beta = .15$, $t = 2.26$). Furthermore, significant positive direct effects of customer knowledge were found on behavioural intention to present ACT Instant ($\beta = .32$, $t = 2.40$) and attitude towards Immerse ($\beta = .22$, $t = 2.66$) (see Table 18 in Appendix J). Therefore, relative advantage and customer knowledge were further investigated using the PROCESS macro for potential new insights.

5.5.1 Exploring Relative Advantage and Customer Knowledge

Relative advantage and customer knowledge were incorporated in exploring new relationships for the proposed conceptual model. Relative advantage had only a significant effect in the case of Immerse, so it was deemed appropriate to explore the relationship for attitude towards Immerse. However, the models need to be equivalent in variables to compare the model results between ACT Instant and Immerse since, for ACT Instant, the relative advantage still impacts the effect of other variables even when it is not significant. Therefore, the relative advantage was incorporated in both studies.

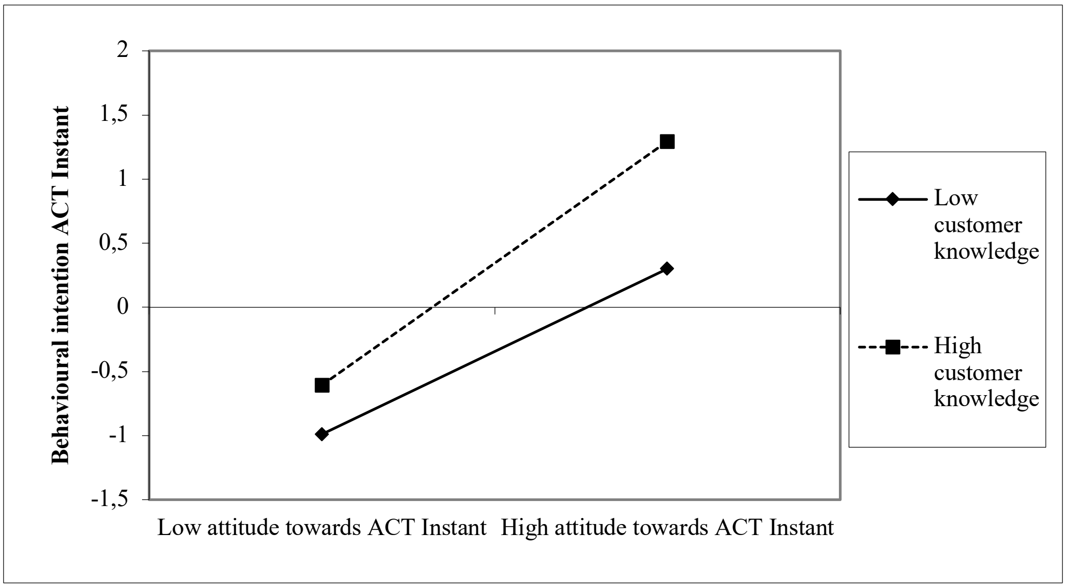
Customer knowledge significantly affected the behavioural intention of ACT Instant and attitude towards Immerse. Therefore, it seemed appropriate to investigate these significant effects further. Customer knowledge is measured by a salesperson's perception of a great understanding of the customer's needs, desires, and behaviours (Böhm et al., 2020). Customer knowledge is closely related to customer stewardship, in which the salesperson feels a sense of ownership and is morally responsible for a customer's overall welfare (Schepers et al., 2012). Therefore, since customer stewardship was hypothesised as a moderator in the conceptual model, it was decided to investigate what influence customer knowledge would have when customer stewardship is replaced with customer knowledge and whether it would act as a moderator.

Tables 19 and 20 in Appendix J present the results of including relative advantage and customer knowledge in the case of ACT Instant and Immerse. Model 1 shows the model's results without interaction effects, used to conclude direct effects and interpret the causal effects from the control variables or mentioned otherwise. Models 2, 3 and 4 are used to investigate the moderating effects of customer knowledge (see Appendix J). Because relative advantage and customer knowledge were further analysed for potential new insights, only new or changed findings will be discussed to avoid repetition.

5.5.1.1 ACT Instant Results

Models 2, 3 and 4 in Table 19 presented a new finding for the interaction effect between attitude towards ACT Instant and customer knowledge (ATTAI × CK). These models showed a positive moderation for customer stewardship on the relationship between attitude towards ACT Instant and behavioural intention to present it (2: β =.18, t = 2.21; 3: β = .21, t = 2.02; 4: β = .25, t = 2.80). This significant moderation means that when a salesperson perceives a high level of customer knowledge, it strengthens the positive relationship between a salesperson's attitude toward ACT Instant and their behavioural intention to present it to the customer compared to a salesperson with a low level of customer knowledge (see Figure 8).

Figure 8 - The interaction effect of attitude towards ACT Instant and customer knowledge



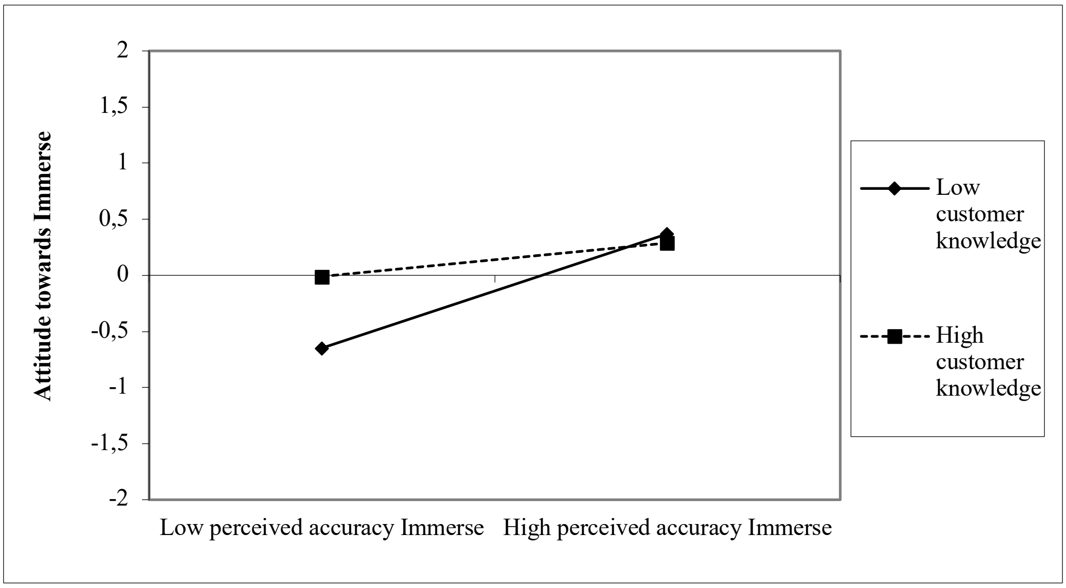
Similar to the no interaction model of ACT Instant (Model 1 in Table 6), geographical region significantly affects behavioural intention to present ACT Instant for AMEA and LATAM. Salespeople who work in Asia, the Middle East and Africa had a significantly lower behavioural intention to present ACT Instant than those who work in Europe (β = -.81, t = -2.32). However, this effect turned out to be not significant when the moderating effects of customer stewardship were included in Models 2, 3 and 4 (2: β = -.54, t = -1.55; 3: β = -.54, t = -1.59; 4: β = -.56, t = -1.68). On the other hand, salespeople who work in Latin America had a significantly higher behavioural intention than those who work in Europe (β = 1.35, t = 2.52). Moreover, different from the no interaction model of ACT Instant (Model 1 in Table 6), a salesperson's involvement in ACT Instant has no significant effect on their behavioural intention to present it (β = -.14, t = -1.62). Models 2, 3 and 4 showed that a salesperson's sales experience had a negative and significant effect on their behavioural intention to present ACT Instant (2: β = -.17, t = -2.06; 3: β = -.17, t = -2.08; 4: β = -.16, t = -1.96). Further analyses indicated that the interaction between attitude towards ACT Instant and customer knowledge (ATTAI × CK) was the main cause of these differences.

5.5.1.2 Immerse Results

Different from testing the conceptual model in the case of Immerse (see Table 8), Model 1 in Table 20 showed that subjective norm does not significantly influence a salesperson's attitude towards Immerse (β = -.00, t = -.03). In return, the relative advantage had a significant and positive effect on attitude towards Immerse (β = .07, t = 2.88). Furthermore, the impact of AI readiness on attitude towards Immerse was marginally significant in Model 1 (β = -.09, t = -1.67) (see Table 20 in Appendix J). Compared to the no interaction model (Model 1), the effect of AI readiness on attitude towards Immerse was significant in Model 2 (β = -13, t = -2.91). Further analyses indicated that the interaction between perceived accuracy and customer knowledge (PAIM × CK) was the main cause of this difference.

Model 2 in Table 20 presented a new finding for the interaction effect between perceived accuracy and customer knowledge (PAIM × CK). The model showed a negative moderation for customer stewardship on the relationship between the perceived accuracy of Immerse and attitude towards it (β = -.22, t = -3.97). This significant moderation means that when a salesperson has a high level of customer knowledge, it weakens the positive relationship between a salesperson's perceived accuracy of Immerse and their attitude towards Immerse to present compared to a salesperson with a low level of customer knowledge (see Figure 9).

Figure 9 - Interaction effect of perceived accuracy of Immerse and customer knowledge



Finally, compared to the conceptual model results in the case of Immerse (Table 8), Model 1 (see Table 20) showed that geographical region had a significant effect on attitude towards Immerse for LATAM. The attitude towards Immerse is significantly higher for salespeople working in Latin America compared to Europe (β = .73, t = 2.07).

6. Discussion

This research examined the reasons behind a salesperson's behavioural intention to present an AI solution. The formulated research question voiced the aim of the research and should be possible to be answered now that the results have been analysed. The research question was formulated as follows:

How can the behavioural intention of a salesperson in a market research organisation to present an AI solution to customers be improved?

This research contributes to the existing literature on human behaviour, technology (or AI) adoption, and salesperson's characteristics in solution selling. It provides several insights into how a salesperson's attitude towards an AI solution can be improved, increasing their behavioural intention to present it. The data used to deliver these insights are gained from MetrixLab sales-, research- and GTIC departments. First, the main findings will be discussed, where the similarities and differences are compared and interpreted. Afterwards, the theoretical and managerial implications of this research will be presented. Finally, limitations and suggestions for further research will be discussed.

6.1 General Discussion Results

Consistent with the fundamental tenet of the TRA framework (Damerji & Salimi, 2021; Fishbein & Ajzen, 1975), the results suggest that attitude towards an AI solution has a positive association with behavioural intention to present it. Further, the results showed that a salesperson's perceived accuracy of the outcomes provided by the AI solutions and subjective norm positively influenced this attitude towards the AI solution, in which the perceived accuracy of the AI solution acts as the strongest driver. Zhu et al. (2014) support this research's finding of perceived accuracy in combination with attitude, as they highlighted that inaccurate recommendations or information would irritate individuals and thus enhance their negative attitudes. Contrary to expectations of social influence, only subjective norm significantly positively affects a salesperson's attitude towards the AI solution, and social identity did not significantly affect their attitude. A possible explanation found in technology adoption literature is that subjective norm is particularly influential in determining an individual's decision to use technology when they have no previous experience yet and, therefore, will tend to rely more on others to decide whether to try out the technology (Cheung & Lee, 2010). In contrast, social identity is more effective when continuous usage behaviour occurs later in the adoption process (Cheung & Lee, 2010). Since AI technology and AI solutions are relatively new, there is no continuous usage behaviour yet.

Moreover, the results showed that subjective norm is not directly related to a salesperson's behavioural intention to present an AI solution to the customer. This implies that attitude towards the AI solution functions as a mediator between subjective norms and behavioural intention. This finding contradicts the original TRA framework, where the subjective norm is a core construct directly influencing behavioural intention. However, the Theory of Planned Behaviour (TPB), an extension of

TRA, included a possible mediation between subjective norm, attitude, and behavioural intention (Ajzen, 1991). Thus, the results of this research align with the TPB (Ajzen, 1991); the effect of opinions from peers or people of importance does not directly change a salesperson's intention to engage in selling the AI solution. Still, these opinions enhance their judgement of the AI, indirectly influencing their intention.

Contradicting with literature (Damerji & Salimi, 2021; Flavián et al., 2022), the results showed that salesperson's AI readiness does not relate to their attitude towards an AI solution, like an ACT Instant and Immerse. This implies that the relationship between AI readiness and attitude towards an AI solution might be more complex than initially thought. Besides the possibility that other variables or contextual factors could significantly influence this relationship, this research measured AI readiness using eight items instead of the literature-recommended 16 items (Damerji & Salimi, 2021). The factor analysis presented difficulties in combining these items in the intended construct. Even though multiple reliability and validity tests were performed, it might be that the combined items did not measure the essence of AI readiness. Accordingly, considering a broader range of items for measuring AI readiness might change the significance of this relationship. In addition, Flavián et al. (2022) investigated the four personality traits of AI readiness, including optimism, inventiveness, discomfort, and insecurity, as separate constructs rather than combining them.

6.1.1 Differences between ACT Instant and Immerse (direct effects)

The results showed significant differences between ACT Instant and Immerse for a salesperson's awareness and relative advantage. While no significant effect was found for a salesperson's awareness on attitude towards ACT Instant, a salesperson's awareness positively and significantly affects their attitude towards Immerse. This indicates that when salespeople are more conscious of, knowledgeable, or informed about AI solutions, they would have a more positive attitude towards Immerse. For ACT Instant, the nature of the AI solution can explain the lack of a significant effect. Since ACT Instant uses AI algorithms to generate outcomes based on the input provided by the customer, it has a "black-box" nature (Shin, 2021). So, even when they gain more knowledge about AI solutions, this specific process cannot become more transparent. This explains why a salesperson's awareness does not significantly influence their attitude towards ACT Instant but positively affects their attitude towards Immerse. Since Immerse uses a discussion platform's AI technology to analyse human responses of large groups in real-time, the salesperson can experience the process themselves in which the AI technology structures the responses. The process becomes more transparent, in which the salesperson can understand the reasoning behind AI predictions, positively influencing their attitude towards Immerse (Shin, 2021).

Further analysis showed no significant effect for relative advantage on attitude towards ACT Instant, whereas relative advantage positively and significantly impacts a salesperson's attitude towards Immerse. ACT Instant is generally known for the price and speed advantages of presenting results. The missing significant effect of relative advantage in the case of ACT Instant indicates that these advantages do not significantly impact a salesperson's attitude towards ACT Instant. Most likely, the significant impact of perceived accuracy and subjective norm dominate, making the impact of relative advantage subordinate. Furthermore, this missing significant effect is substantiated by the previously presented quotes of interviewees, where doubts concerning these advantages dominate the tone. On the other hand, insights from the preliminary interviews can also explain the additional insight for Immerse. Interviewees explained the advantages of using Immerse for finding customer solutions. The positive relationship between perceived relative advantage and their attitude towards Immerse is illustrated in the following quote, where the interviewee explains how Immerse uses AI technology and how this advantages them hinting at the positive attitude:

> *"I think Immerse could have given a better answer because there are more opportunities to seek that depth simply with AI. First, the individual response is analysed: what do you think about this product? Then the participant is shown all the answers of the others; then again, the AI asks: now that you hear this from others, what do you think about that now? So, we can find more deepness much better and quicker."* (Salesperson 2)

6.1.2 The Role of Customer Stewardship

Customer stewardship indirectly affects a salesperson's behavioural intention to present ACT Instant differently than their intention to present Immerse, suggesting that the role of customer stewardship depends on how AI technology is employed to compose the AI solution. This assumption is based on the inconsistent findings from the reported moderation analyses between ACT Instant and Immerse for customer stewardship.

For ACT Instant, the results showed that when a salesperson has a high level of customer stewardship, their behavioural intention to present ACT Instant is more strongly influenced by their level of attitude towards it (see Figure 5). This finding contradicts what Schepers et al. (2012) addressed, in which the customer's welfare precedes personal beliefs or preferences. However, this finding suggests that when a salesperson develops a high sense of ownership and feels morally responsible for the customer, they are more motivated to provide their own opinion on the best-perceived solution. According to Hoeber and Schaarschimdt (2017), this motivation is caused by their aim to maintain a long-term relationship. So, salespeople with high customer stewardship are most likely to improve their willingness to present ACT Instant as a consequence of a positive attitude towards it. As shown in previous results, this attitude is formed based on their perceived accuracy of ACT Instant's outcomes and subjective norm, with their perceived accuracy as the most vital driver for this attitude.

For Immerse, the results showed that when a salesperson has a high level of customer stewardship, their attitude towards Immerse is less influenced by their perceived accuracy of Immerse. This implies that when a salesperson develops a high sense of ownership and feels morally responsible for ensuring the solution meets the customer's needs and preferences, this does not make them more focused on the accuracy of outcomes and predictions of the Immerse. The accuracy of Immerse becomes less critical, and the AI used in the solution is seen more as the gimmick of the solution that drives their attitude. This effect can be seen in Figure 7, where the influence of perceived accuracy flattens in the case of a high level of customer stewardship. This finding contradicts expectations, where customer stewardship would strengthen the relationship between perceived accuracy and attitude towards the AI solution.

These unexpected differences implicate the contrast between the importance of their accuracy perception for the two solutions. The nature of the AI solutions explains these differences, as ACT Instant and Immerse differ in their use of AI technology. Whereas ACT Instant uses AI's machine learning elements to generate outcomes, Immerse uses a discussion platform's AI technology to analyse human responses of large groups in real time. These various natures of the AI solution imply that when a salesperson has a high customer stewardship level, and the AI solution includes human input and the technology acts as an additional feature, their accuracy will less impact their attitude before they are willing to present the AI solution. However, when a salesperson has a high customer stewardship level, and the outcomes are AI-generated, their attitude will be more critical, and indirectly they should perceive a high accuracy before they are willing to present the AI solution.

Moreover, although it was expected at the beginning of this research that customer stewardship would negatively influence the relationship between subjective norm or social identity and behavioural intention, no significant effects were found. However, since no significant direct effects were found between subjective norm and a salesperson's behavioural intention and the relationship between social identity and a salesperson's behavioural intention, it makes sense that customer stewardship does not moderate these relationships.

6.1.3 The Role of Customer Stewardship versus Customer Knowledge

The previous section showed that customer stewardship did not moderate the relationships as expected. However, why customer stewardship showed these contradicting effects was still vague and incomprehensible. Therefore, the further analysis involved customer knowledge as a moderator, testing it on the same relationships as customer stewardship to provide explanations for the contradicting and unexpected results. The moderation analyses of customer knowledge showed the same discrepancies in the case of significance for ACT Instant and Immerse compared to the moderation effect of customer stewardship. Customer knowledge positively and significantly moderated the relationship between a salesperson's attitude towards ACT Instant and their behavioural intention to present it, and customer knowledge negatively and significantly moderated the relationship between the perceived accuracy of Immerse and a salesperson's attitude towards it.

For ACT Instant, the significant moderation effect of customer knowledge suggests that a salesperson with a great understanding of the customer's needs, desires and behaviours, their behavioural intention to present ACT Instant is more strongly influenced by their level of attitude towards ACT Instant (see Figure 8). Salespeople with high customer stewardship emphasise building customer trust and transparency, aiming to maintain a long-term relationship with the customer (Hoeber & Schaarschmidt, 2017). Due to the long-term relationship, the salesperson knows more about the customer's needs, desires, and behaviours, giving the salesperson more control over the sales process and decreasing the risk of detriment. Besides, when the salesperson has low customer knowledge, the risk of detriment is higher as their estimation of the needs, desires and behaviours is based on less information. As mentioned, their attitude is mainly based on their perceived accuracy of ACT Instant's outcomes. So, the more the salesperson believes that ACT Instant could provide the desired accurate outcomes, the higher their attitude towards it. Therefore, when there is this long-term relationship in which the salesperson has a greater understanding of the customer and has this positive attitude towards ACT Instant, their confidence in presenting it as an option would increase. As they know the customer's needs, desires, and behaviours, they could later still influence the after-sales process when, for example, ACT Instant does not provide the desired outcomes. However, this would only happen when they have a positive attitude towards ACT Instant in the first place. They are less willing to present ACT Instant when they have a high customer knowledge and a negative attitude. This finding contributes to the results of the significant moderation of customer stewardship, in which the salesperson's feeling of being morally responsible for the overall welfare of the customer enhances the importance of their attitude before being willing to present it.

For Immerse, the significant moderation effect suggests that a salesperson with a great understanding of the customer's needs, desires, and behaviours their attitude towards Immerse is less influenced by their perceived accuracy of Immerse (see Figure 9). This finding contributes to the results of the significant moderation of customer stewardship. As mentioned above, customer knowledge is closely related to a long-term relationship between the customer and the salesperson. Creating and maintaining a long-term relationship requires genuinely understanding the customer's needs, desires, and behaviours. A salesperson with high customer knowledge understands the customer's needs and preferences, making it easier to meet them. Therefore, they are less focused on the accuracy of outcomes and predictions of the Immerse since they do not entirely depend on the outcomes, and AI technology is an additional feature to speed up data processing. The interpretations of outcomes can be loosely interpreted, as they understand the customer's needs and preferences. Therefore, this explains why when a salesperson develops a high sense of ownership and feels morally responsible for ensuring the solution meets the customer's needs and preferences, it makes them less focused on the accuracy of outcomes and predictions of the Immerse.

As similar effects occurred in the case of customer stewardship and customer knowledge, these two constructs seem to be highly compatible and reinforce each other. Chapter 4.6.3 showed that customer stewardship and customer knowledge had a strong significant correlation suggesting coherency exists between the variables. However, the explanations of these effects are based on logical reasoning that follows from combining the analysis results and the interview's observations and insights. Future research is needed to provide support for these assumptions.

6.2 Theoretical Implications

This research discovered exciting results and insights, which increase the understanding of the solution-selling process from a salesperson's perspective and offers insightful theoretical implications. This research contributes to the literature by being the first to empirically examine how a salesperson's attitude towards an AI solution can be influenced to improve their behavioural intention in presenting it. The following section will elaborate on the theoretical implications of the findings.

First, although various studies used the TRA of Fishbein and Ajzen (1975) for understanding the selling behaviour of salespeople or for understanding technology adoption, the integration of technology adoption in understanding the selling behaviour of salespeople in solution selling lacked empirical support. For example, Zhu et al. (2014) incorporated perceived accuracy for customer decision-making purposes, in which the customer's attitude was influenced by their perceived accuracy of the provided information and recommendations. This research also focussed on how a salesperson's attitude was influenced by their perception of the solution's accuracy of the provided information and recommendations. However, their perception of the accuracy was used to assess the solution's value for someone else, namely their customers, instead of themselves. The significant findings of this research for perceived accuracy add to the technology, specifically AI, adoption literature in combination with solution selling.

Second, various studies investigating the solution-selling process pointed out the importance of the salesperson's feeling of responsibility and the mutual trust between a salesperson and their customers to strengthen and maintain long-term relationships (Hoeber & Schaarschmidt, 2017; Koponen et al., 2019). However, the inclusion of customer stewardship in a solution-selling context was not yet explored. Therefore, it adds to our understanding that customer stewardship impacts the solution-selling process of a salesperson. However, the contradicting results highlighted the need for future research to explore how customer stewardship is involved in solution selling.

Finally, this research's focus on AI solutions provides valuable insights into the literature. To our knowledge, this research was the first to explore the selling process of solutions that involve AI. Furthermore, the comparison between how AI technology is employed to compose the AI solution and how this affects selling behaviour has not been made yet.

6.3 Managerial Implications

This section presents the managerial implications that follow from the previously described results. Recommendations for further actions will be suggested based on these results, including the desired effects of these actions.

6.3.1 General Managerial Implications of AI Solutions

Because a salesperson's behavioural intention to present an AI solution is based on their attitude towards it, it is suggested that market research organisations focus on increasing their attitude. To change this attitude towards an AI solution, they should improve a salesperson's perceived accuracy of the outcomes provided by an AI solution and subjective norm since this positively influences their attitude towards an AI solution, enhancing their behavioural intention to present it to customers. As the perceived accuracy of a salesperson is the strongest driver, market research organisations should primarily focus on changing this. This research suggests two possible actions to change a salesperson's perceived accuracy.

First, market research organisations could try to change a salesperson's perception of the solutions by promoting transparency since the lack of transparency of AI creates doubts and difficulties in accepting them (Shin, 2021). Communicating clearly about the sources of AI technology, the method used to verify the data, and any limitations or uncertainties in the AI solutions, helps salespersons gain confidence that the outcomes are accurate. Creating transparency in AI solutions can also be done by providing training- and trial sessions. These sessions include providing detailed information about the AI solution, explaining and showing how it works, and answering questions. These sessions would increase their awareness of the solution, although results showed that this did not significantly impact solutions where the outcomes are AI-generated, like ACT Instant. However, these training- and trial sessions primarily intend to create more evidence of the accuracy and to set new boundary conditions for AI solutions. Interpreting the interview responses suggest that the salespeople's perception of accuracy at MetrixLab is primarily based on anecdotal evidence, in which they form their convictions on misconceptions and non-comparable situations. By showing them examples, trials or mock-up cases of the AI solutions, in different situations, for various types of customers and mixed customer questions, the salesperson would gain more trust and adjust their perception of the accuracy of the AI solutions. Furthermore, these examples, trials or mock-up cases of the AI solutions would increase the subjective norm as there will be social proof. In these sessions, they can discuss and evaluate the advantages and disadvantages of using AI solutions in different situations, which would change their assumptions of the solution's accuracy based on non-comparable situations and misconceptions. These discussions in the sessions would also increase the subjective norm due to social activation and social proof. Engaging the salespeople in these sessions would increase involvement in AI solutions and the subjective norm, positively influencing their attitudes and behavioural intentions.

Second, market research organisations could increase the actual accuracy of AI solutions instead of solely changing the salesperson's perception. Changing the accuracy of the AI solution could only be managed over time as AI technology constantly evolves and improves. So, this recommendation would take some time. However, these organisations need to try adapting the solution to the newest updates of AI technology regarding accuracy. Nevertheless, market research organisations can use the sessions to discuss and evaluate AI solutions, as mentioned before, but also to provide an opportunity to give anonymous feedback. They should encourage salespeople to provide feedback on AI solutions and ensure they act on their feedback regarding the AI solution's accuracy, creating involvement which influences their behavioural intentions. After changing the solutions and increasing the accuracy of the AI-generated outcome, market research organisations should still provide training- and trial sessions to show examples, trials or mock-ups of the solutions, as mentioned in the first recommendation, to provide the evidence of the accuracy. Otherwise, the perception of salespeople would not be changed, and the same problems occur.

6.3.2 Specific Managerial Implications of MetrixLab's AI Solutions

Besides improving a salesperson's perceived accuracy of the outcomes and subjective norm, this research found that improving a salesperson's attitude towards an AI solution and their behavioural intention to present it depends on how AI technology is employed to compose an AI solution. Hence, market research organisations must indicate how AI technology is used to compose the solution before considering other actions. They should especially learn how to deal with a salesperson's customer stewardship, as the role of customer stewardship depends on how AI technology is employed to compose the AI solution. Since these differences between the use of AI technology are specific to MetrixLab's solutions, further recommendations will be presented towards them. Other market research organisations should test and gain insights first into how they use AI technology in their AI solutions.

MetrixLab could deal with a salesperson's customer stewardship by differentiating the level of their customer stewardship for each customer. From the literature, it can be assumed that their customer stewardship level is probably lower for new customers with whom they do not yet have a long-term trusting relationship. However, MetrixLab should, before acting on this assumption, gain more evidence by having conversations with the salespersons concerning their feelings of responsibility for which type of customers. So, by identifying the level of customer stewardship for each customer, they can give direction to the salesperson on which customers they should present the AI solution. As MetrixLab experiences that especially ACT Instant is not adopted, and the interviews revealed a negative attitude towards it due to the lack of perceived accuracy, they should focus on targeting the customers where salespeople have low customer stewardship for presenting the solution. Focusing on these types of customers and presenting ACT Instant as a pilot indirectly improves a salesperson's perceived accuracy. These customers will provide feedback and additional information on the solution, which creates a kind of new evidence, increasing the salesperson's belief in ACT Instant's accuracy. Therefore, MetrixLab could, by differentiating the level of their customer stewardship for each customer and focusing on these types of customers, increase the attitude and behavioural intention of the salespersons.

Finally, MetrixLab sees a high demand for AI solutions, such as Immerse, to speed up data processing, but experienced that sales of their AI solution, ACT Instant, are lagging. Based on the significant differences in the results between ACT Instant and Immerse and the interview's observations and insights, MetrixLab could introduce an intermediate version of ACT Instant. The interviewees expressed significant differences in their perceived accuracy and attitude between ACT Instant and

Immerse, in which they were way more positive towards Immerse. Hence, the transition to an AI solution in which AI algorithms are indispensable to predict outcomes, like ACT Instant, seems too revolutionary for their salespeople. As Immerse combines AI technology with human (respondents) input and is more socially accepted, it would be a final suggestion that MetrixLab also introduces an intermediate version of ACT Instant where AI technology acts as an additional feature combined with human input.

6.4 Limitations

Various issues during the development of this research occurred that are relevant to the outcome of the results. Despite the promising results, this section highlights several limitations, which explain in detail the value of the results.

First, the independent variables in the conceptual model were hypothesised separately, and no relationships between these constructs were determined. However, based on the multiple strong significant correlations, it can be assumed that coherency exists between the variables. Besides, the hypotheses were disaggregated and tested separately on both solutions since the preliminary interviews revealed that the respondents would answer differently depending on the solution for the statements related to perceived accuracy, attitude towards AI solutions, and behavioural intention. However, the results showed a significant difference between ACT Instant and Immerse for a salesperson's awareness and relative advantage. This difference in awareness and relative advantage could be better explained when a distinction in the questionnaire items between ACT Instant and Immerse was made, same as for perceived accuracy, attitude and behavioural intention was done, instead of the general AI solutions statements. For example, the respondents can think that they have a generally great understanding of AI solutions, as the items were not specified for these constructs. Therefore, it cannot be concluded that the responses and results are entirely accurate. Possibly, more undiscovered relationships exist that could help understand the salesperson's behavioural intention.

Second, this research's focus is on salespeople's behavioural intentions. However, as the data were gathered within a single company, the tested sample included other departments. Due to the expected low response rate of questionnaires, a minimum sample population of 200 was suggested. Hence, without including the other departments, the sample was too small. Although no significant differences between the departments were found, this could have still affected the results. Thus, precaution is needed in generalising the results as the data were gathered within a single company and the tested sample variations.

Third, the sample size exceeded the required Cochran's (1977) sample size for continuous data. However, multiple actions were required to retrieve this number of responses since various issues were raised when the questionnaire was sent to the sample. The multi-mailer system used a different format than was familiar for the sample. Besides, with the first reminder, a mistake was made in which the supervisor's email address was presented differently. Hence, people notified the supervisor that they initially thought the invitation and first reminder were spam. To solve this issue, the supervisor personally requested the people who had not completed the questionnaire yet, to participate in the questionnaire. This action led to the non-response bias, as two significant effects emerged in this research, meaning that this bias possibly affected the data. Even though Podsakoff et al. (2003) proposed that not all constructs were likely to be impacted by response biases, the research results should be evaluated carefully.

Fourth, a fuller understanding of the salesperson's behaviour would require the validity of the conceptual model and the questionnaire across the various countries (Steenkamp & Baumgartner, 1998). The questionnaire was controlled for the salesperson's nationality and geographical region because MetrixLab is a global company with employees in 23 countries worldwide. However, the results did not consider measurement invariance, which could have affected the interpretation. For example, cross-national variations in scale could have occurred due to actual differences between countries on the underlying construct or systematic biases in how individuals from different countries responded to specific items (Steenkamp & Baumgartner, 1998). Besides, cross-national variations in relationships between scale scores may have pointed to actual variations in the structural relations between the constructs, differences in scale reliability, or even non-equivalence of the related constructs (Steenkamp & Baumgartner, 1998). Therefore, future research should consider the six levels of measurement invariance (e.g., configural invariance, metric invariance, scalar invariance, factor covariance invariance, factor variance invariance, and error variance invariance) for testing the applicability of the results across countries and generalising the results.

Finally, the data were tested within the range of statistical knowledge in SPSS Statistics using the PROCESS Macro. As mentioned, transforming the data into the intended factors presented various problems. Therefore, possibly items were included or excluded affecting the overall data reliability and validity. Besides, PROCESS Macro is a modelling tool that facilitates different templates for testing the moderation and mediation interactions. However, as mentioned, only one moderation interaction could be measured on the relationships between the independent variable (X), mediator (M) and the dependent variable (Y), which complicated investigating customer stewardship. The decision was made to split up the moderating interaction effects using Models 58 and 15. However, possibly other templates could have shown better understanding results. This assumption is based on the unexpected and unexplained varying results between the models that tested the interaction effect between Attitude towards ACT Instant and customer stewardship (ATTAI × CS).

6.5 Future Research

As hinted in the results discussion section, the results of this research provide suggestions and directions for future research. This section will elaborate on these suggestions.

First, as mentioned, this research's limitation is that it was conducted in one organisation with a corresponding low sample size. Therefore, the results need to be generalised with precaution. The results will be more generalisable by conducting future research in similar market research organisations or in different B2B contexts where AI solutions are sold. Besides, this research compared only two specific solutions of MetrixLab. The introduction already hinted at the many possibilities of using AI technology; hence, future research could test multiple AI-generated solutions to generalise this research's implications without precaution.

Second, the contradicting and unexpected findings for customer stewardship suggest the need for future research. Besides, it could be valuable for future research to investigate customer stewardship's effect on the relationship between the subjective norm and attitude towards the AI solution since the results imply that attitude towards the AI solution functions as a mediator between subjective norms and behavioural intention. Besides, the constructs of customer stewardship and customer knowledge seem highly compatible and reinforce each other. Further investigation of these assumptions is needed to support this assumption.

Third, the TRA framework initially intends to understand the actual behaviour (Fishbein & Ajzen, 1975). The selling behaviour process of the AI solution would involve multiple external factors, such as the influence of (potential) customers and the involvement of competitors. Because of external factors, each actual selling moment is different. For example, before a potential customer buys the AI solution, the customer needs to adopt the presented outcomes and predictions of the AI solution. Besides, this selling process would include the adoption process of the customer, which was outside of this scope. Furthermore, a customer could be influenced by, for example, the other competitors with a cheaper offer, which influences the selling behaviour of the salesperson since they need to adapt to the situation. As these external factors were beyond reach that were required for investigating the salesperson's behaviour, this research solely focused on the behavioural intention of a salesperson presenting the AI solution to the customer and excluded the actual selling behaviour. However, it could be valuable for future research to include the customer adoption process to create a more comprehensive understanding of the salesperson's selling behaviour.

Finally, future research may use an intervention approach to provide a detailed step-by-step plan to implement the recommendations of this research. This could be valuable as interventions focus on individual behaviours and how environmental changes can support those behaviours. Therefore, future research may use an intervention approach to investigate the recommended training- and trial sessions as a tool to increase salespeople's perception of the accuracy and affect their behavioural intention.

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Appendix A

The formula uses two key factors: the margin of error and the alpha level (Cochran, 1977). The margin of error (also known as the confidence level) signifies the risk the researcher is willing to accept in their research. The general rule relative to acceptable margins of error is for continuous data 3%. The alpha level refers to "the level of acceptable risk the research is willing to accept that the true margin of error exceeds the acceptable margin of error" (Bartlett et al., 2001, p. 44). Most educational research studies use an alpha level of .05 or .01. Below, Cochran's (1977) sample size formula for continuous data is presented, along with explanations of how these decisions were made.

$$n_0 = \frac{(t)^2 * (s)^2}{(d)^2} = \frac{(1.96)^2(1.167)^2}{(7*.03)^2} = 118$$

Where t = value for selected alpha of .025 in each tail = 1.96.

Where s = estimate of standard deviation in the population = $\frac{7\ (number\ of\ points\ on\ the\ sale)}{6\ (number\ of\ standard\ deviations)}$ = 1.167.

Where d = acceptable margin of error for mean being estimated = number of points on primary scale $*$ acceptable margin of error.

$$n = \frac{n_0}{(1+\frac{n_0}{pop.})} = \frac{118}{(1+\frac{118}{198})} = 74$$

Where pop. = population size = 198.

Where n_0 = required return sample size according to Cochran's formula = 118.

Where n = required return sample size.

Appendix B

Hi [First name],

Artificial Intelligence (AI) has exciting possibilities and opportunities in market research. MetrixLab is always looking to innovate and is curious about its potential!

This curiosity drove Jolique Weelink and Carlijn Tummers to invite me to write my master thesis about the adoption of AI solutions at MetrixLab.

How can you help?
We are eager to find out how you feel about MetrixLab's AI solutions. It would be great if you could share your opinion via this survey link. The questionnaire is anonymous and will take about 10 minutes of your time.

Please participate before April 1st. If you do, you have the chance to win one of the five books "Better Brand Health" from Jenni Romaniuk!

Thanks in advance for your time!

Kind regards,

Myrthe van Bergen | Intern Innovation Management
Rotterdam, The Netherlands | T (+31) 10 203 700

Appendix C

Hi [first name],

Artificial Intelligence (AI) has exciting possibilities and opportunities in market research. MetrixLab is always looking to innovate and is curious about its potential! That is why Myrthe van Bergen shared a questionnaire with you to fully understand the adoption of AI solutions and opportunities for our company.

So, don't forget to complete the questionnaire before April 1st to have the chance to win one of the five books "Better Brand Health" of the Ehrenberg-Bass Institute for Marketing Science!

Please, follow the link below to access the questionnaire:

[LINK]

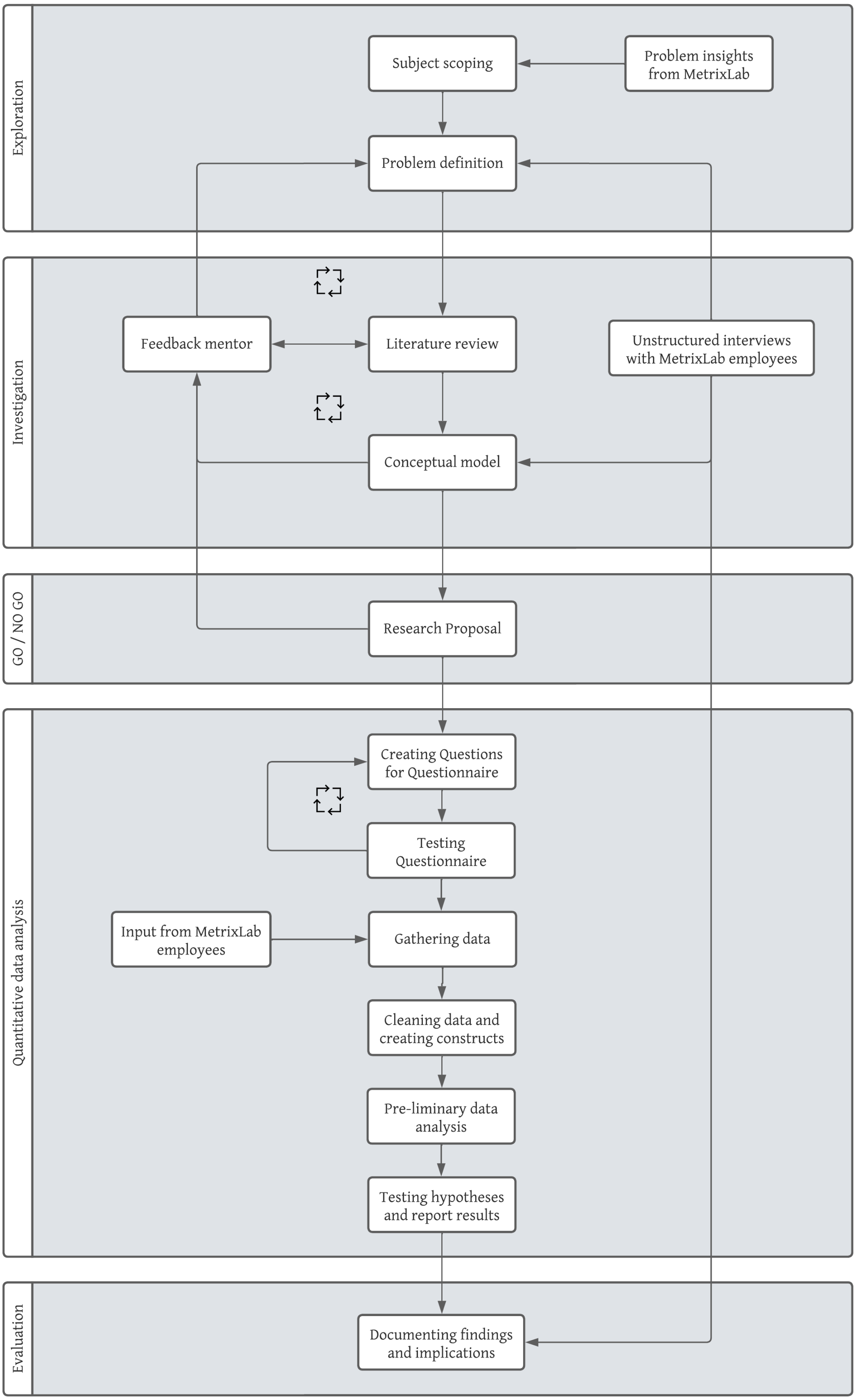
Many thanks in advance for your time and effort!

Best regards,

Jolique Weelink | Global Director Technology, Innovation & Consultancy
Rotterdam, the Netherlands | T (+31) 10 203 700

Appendix D

Figure 10 - Research process



Appendix E

Table 11 - Questionnaire items, original items, and references

Construct	Statements/Questions	Original item	Adapted from
AI readiness			
AIR1	AI technology contributes to a better quality of work.	New technologies contribute to a better quality of life.	Damejri & Salimi (2021)
AIR2	AI technology gives people more control over their daily activities at work.	Technology gives people more control over their daily lives.	Damejri & Salimi (2021)
AIR3	In general, I am among the first in my team to acquire new AI technology when it appears.	In general, I am among the first in my circle of friends to acquire new technology when it appears.	Damejri & Salimi (2021)
AIR4	I keep up with news of the latest AI technological developments in my area of interest.	I keep up with the latest technological developments in my area of interest.	Damejri & Salimi (2021)
AIR5	With AI technology, I often risk putting more effort into understanding something that is not worth it. (Rev.)	With new web technology, I often risk paying a lot of money for something that is not worth much.	Vize et al. (2013)
AIR6	The hassle of understanding new AI technology is usually not worthwhile for me. (Rev.)	The hassle of getting new web technology work for me usually makes it not worthwhile.	Vize et al. (2013)
AIR7	AI technology lowers the quality of the relationship between people by reducing personal interaction. (Rev.)	Technology lowers the quality of relationship by reducing personal interaction.	Damejri & Salimi (2021)
AIR8	I do not consider it safe to do any kind of business with AI technology. (Rev.)	I do not consider it safe to do any kind of financial business with my WSSP online.	Vize et al. (2013)
Awareness			Flavián et al. (2022)
AW1	I am very aware of the abilities and possibilities of MetrixLab's AI solutions.	Before reading the description, I was very aware of robo-advisor services.	
AW2	I have a great deal of knowledge about MetrixLab's AI solutions' abilities and possibilities.	Before reading the description, I had a great deal of knowledge about robo-advisors.	
AW3	I can quickly recall and provide information I have received about the abilities and possibilities of MetrixLab's AI solutions.	Before reading the description, I could quickly recall previous information I had received about robo-advisors.	
Relative advantage			To & Ngai (2006)
RA1	Presenting an AI solution as an option to clients increases future business opportunities for MetrixLab.	Respondents indicated relative advantage of adopting online retailing, regarding the increase of business opportunities.	
RA2	I believe that presenting an AI solution as an option to clients improves business goodwill for MetrixLab.	Respondents indicated relative advantage of adopting online retailing, regarding the improvement in goodwill.	
RA3	I believe that an AI solution adds value to clients.	Respondents indicated relative advantage of adopting online retailing, regarding the value added to customers.	
Social influence			
SI1	Peers who are important to me would think that presenting an AI solution as an option to clients is ____	Peers who are important to me would think that I should use AI.	Cao et al. (2021)

SI2	Peers who influence my behaviour would think that presenting an AI solution as an option to clients is ____	Peers who influence my behaviour would think that I should use AI.	Cao et al. (2021)
SI3	My superiors to whom I report to would think that presenting an AI solution as an option to clients is ____	My superiors to whom I report would think that I should use AI.	Cao et al. (2021)
SI4	How would you express the degree of overlap between your personal identity and the identity of your team?	How would you express the degree of overlap between your personal identity and the identity of the group when you are actual part of the group and engaging in group activities?	Chueng & Lee (2010)
SI5	How attached are you to your team?	How attached are you to the group?	Chueng & Lee (2010)
SI6	I am a valuable member of my team.	I am valuable member of the group.	Chueng & Lee (2010)
Attitude towards AI solution			
ATT1AI	Presenting ACT Instant as an option to clients is valuable.	Using AI-based recommendation systems for making investment decisions is a good idea.	Chua et al. (2023)
ATT2AI	Presenting ACT Instant as an option to clients is a smart idea.	Using AI-based recommendation systems for making investment decisions is a wise idea.	Chua et al. (2023)
ATT3AI	I am open to present ACT Instant as an option to clients.	I am open to use AI-based recommendations for making investment decisions.	Chua et al. (2023)
ATT4AI	My attitude towards ACT Instant is positive.	My attitude towards the new brand is positive.	Wieseke et al. (2007)
ATT1IM	Presenting Immerse as an option to clients is valuable.	Using AI-based recommendation systems for making investment decisions is a good idea.	Chua et al. (2023)
ATT2IM	Presenting Immerse as an option to clients is a smart idea.	Using AI-based recommendation systems for making investment decisions is a wise idea.	Chua et al. (2023)
ATT3IM	I am open to present Immerse as an option to clients.	I am open to use AI-based recommendations for making investment decisions.	Chua et al. (2023)
ATT4IM	My attitude towards Immerse is positive.	My attitude towards the new brand is positive.	Wieseke et al. (2007)
Behavioural intention to present an AI solution			Venkatesh et al. (2003)
BI1AI	I intend to present ACT Instant as an option to clients in the future.	I intend to use AI in the near future.	
BI2AI	I will always try to present ACT Instant as an option to clients.	I will always try to use AI in my workplace.	
BI3AI	I plan to present ACT Instant as an option to clients frequently.	I plan to use AI frequently.	
BI1IM	I intend to present Immerse as an option to clients in the future.	I intend to use AI in the near future.	
BI2IM	I will always try to present Immerse as an option to clients.	I will always try to use AI in my workplace.	
BI3IM	I plan to present Immerse as an option to clients frequently.	I plan to use AI frequently	
Perceived accuracy			
PA1AI	I think that the outcomes and predictions produced by ACT Instant are accurate.	I think the contents produced by algorithms are accurate (accuracy).	Shin (2021)
PA2AI	Recommendations based on outcomes of ACT Instant are in general precise.	Recommended items by algorithm systems are in general precise (accuracy).	Shin (2021)
PA3AI	The outcomes and predictions of ACT Instant are ____ than survey solutions using solely human output.	AI-based recommendation systems are more accurate than human beings.	Chua et al. (2023)

PA1IM	I think that the outcomes and predictions produced by Immerse are accurate.	I think the contents produced by algorithms are accurate (accuracy).	Shin (2021)
PA2IM	Recommendations based on outcomes of Immerse are in general precise.	Recommended items by algorithm systems are in general precise (accuracy).	Shin (2021)
PA3IM	The outcomes and predictions of Immerse are ____ than survey solutions using solely human output.	AI-based recommendation systems are more accurate than human beings.	Chua et al. (2023)
Customer stewardship			
CS1	I feel accountable for the results of my clients.	I feel accountability for the results of my customers.	Schepers et al. (2019)
CS2	I feel a sense of responsibility for the results of my clients.	I feel a sense of responsibility for results of my customers.	Schepers et al. (2019)
CS3	I feel a sense of ownership of my client's problems.	I feel a sense of ownership of the customer's problems.	Schepers et al. (2012)
CS4	I feel responsible for client welfare.	I feel responsible for customer welfare.	Schepers et al. (2012)
Customer knowledge			Böhm et al. (2020)
CK1	I am particularly knowledgeable about my clients' business.	In my job, I am recognized as being skilled in being particularly knowledgeable concerning customers' business.	
CK2	I have a profound understanding of my clients' business goals and preferences.	In my job, I am recognized as being skilled in having a profound understanding of customers' business goals	
CK3	I have a deep understanding of my clients' business processes and operations.	In my job, I am recognized as being skilled in having a deep understanding of customers' business processes and operations.	
Selling target			MetrixLab
ST1	Since I have a selling target, I prefer to present my clients a solution with a high booking value.		
ST2	If I have already reached my selling target, I have no preference in which solution I would present to my clients.		
ST3	Since the booking value for selling AI solutions is lower than for survey solutions, I prefer to present my clients a solution with a high booking value.		
Intrinsic motivation			Mallin & Pullins (2009)
IM1	When I perform well in selling solutions, I know it's because of my own desire to achieve.	When I perform well, I know it's because of my own desire to achieve.	
IM2	I sell because of the feeling of performing a useful service.	I sell because of the feeling of performing a useful service.	
IM3	I obtain a sense of accomplishment from selling solutions.	I obtain a sense of accomplishment from my work.	
Demographics			
GENDER	What gender do you identify as?		
AGE	What is your age?		
NATIO	What is your nationality?		
GEOREG	In what geographical region do you work?		
DEP	At which department of MetrixLab are you working?		
WEXP1	How many years of work experience do you have?		

WEXP2	How many years have you been involved in the sales process of products/services/solutions at MetrixLab?
INV1	How often have you been involved in presenting ACT Instant to a customer?
INV2	How often have you been involved in presenting Immerse to a customer?

Appendix F

Figure 11 - Introduction text

Welcome, and thank you for participating in this questionnaire!

This questionnaire is set up on behalf of my thesis for my masters in Innovation Management at Eindhoven University of Technology. The questionnaire is divided into 8 small sections, and it will take approximately 10 minutes to read the instructions and complete the questionnaire. In this questionnaire, I am interested in your opinion on MetrixLab's AI solutions.

If you have any remaining questions or want more information about this research, the design, or the results, you can contact me via myrthe.bergen@metrixlab.com or by Microsoft Teams.

By clicking on the continue button, you confirm your acceptance.

Figure 12 - Question type: Card Test

The following statements concern Artificial Intelligence (AI) in general. AI is already deeply embedded into everyday life and work. Even small changes in the workplace are made possible by AI, such as spam filters and smart email categorisation. Since AI is a broad concept that can be deployed in various ways, it is essential to consider your working environment and its deployment possibilities.

Please indicate the extent to which you agree with the following statements by dragging and dropping the card to the answer box of your choice. You can put more than one card in the same answering box and not all boxes need to be filled.

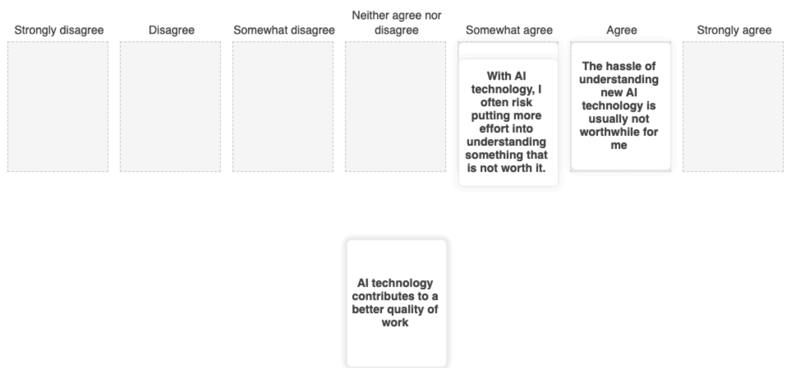


Figure 13 - Question type: Radio Group

Figure 14 - Question type: Dynamic Quiz

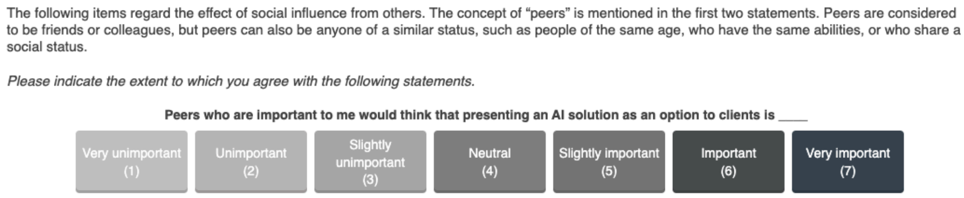


Figure 15 - Question type: Image Picker

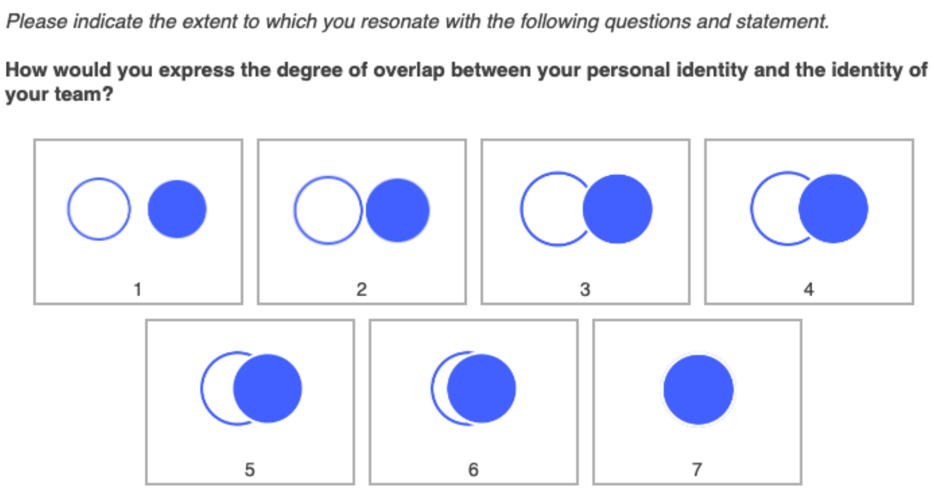
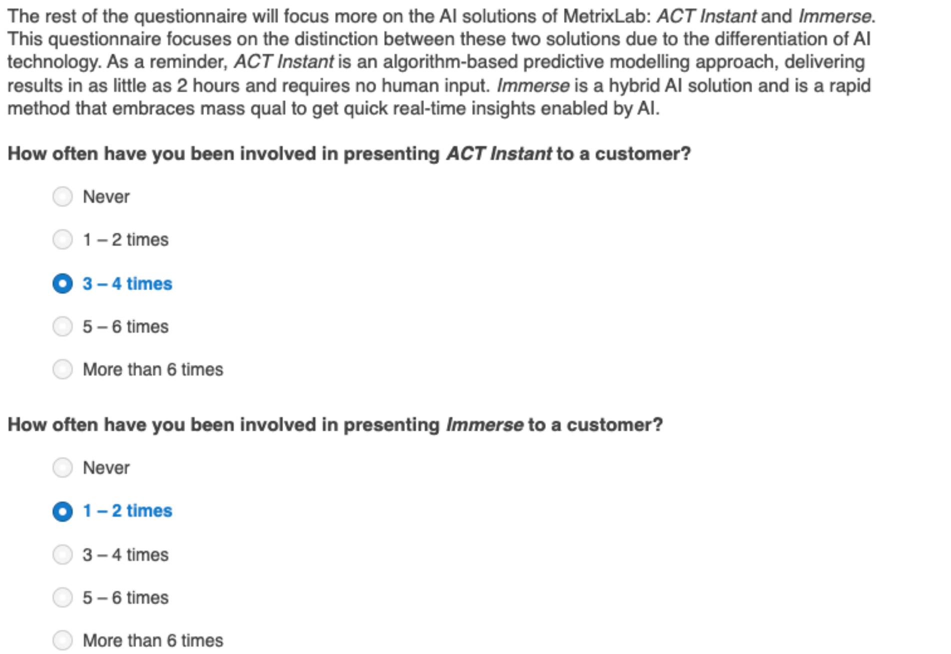


Figure 16 - Question type: Radio



The rest of the questionnaire will focus more on the AI solutions of MetrixLab: *ACT Instant* and *Immerse*. This questionnaire focuses on the distinction between these two solutions due to the differentiation of AI technology. As a reminder, *ACT Instant* is an algorithm-based predictive modelling approach, delivering results in as little as 2 hours and requires no human input. *Immerse* is a hybrid AI solution and is a rapid method that embraces mass qual to get quick real-time insights enabled by AI.

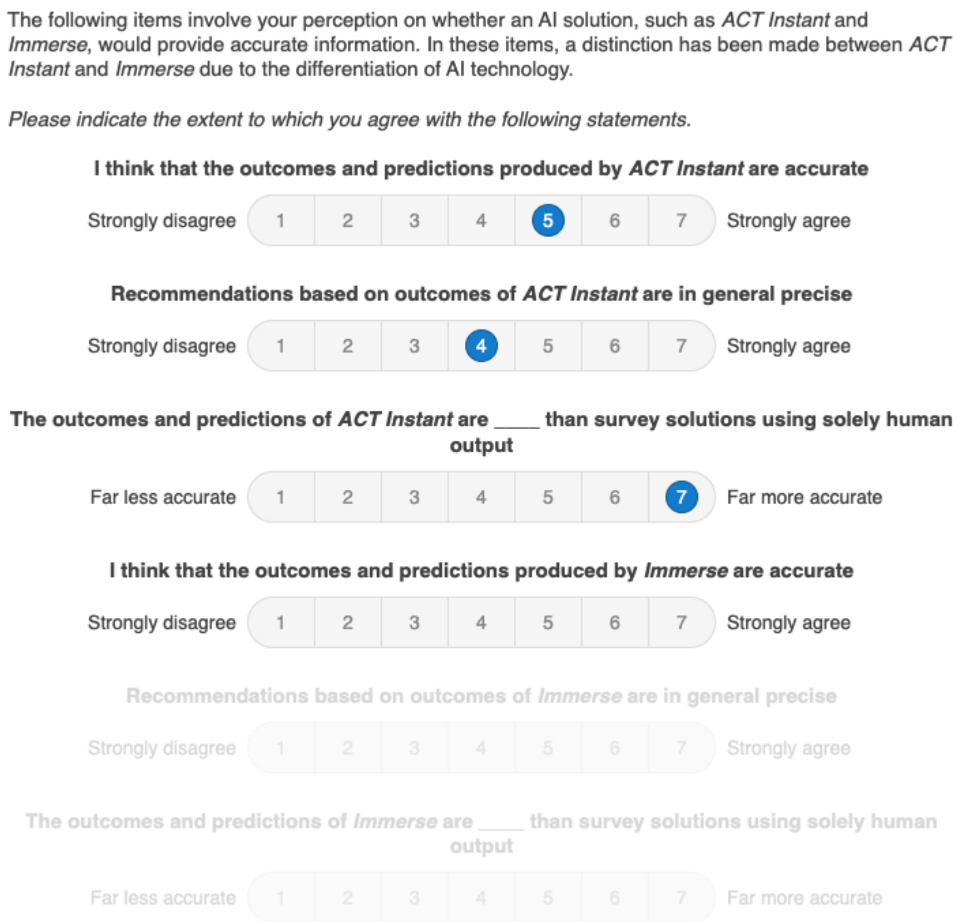
How often have you been involved in presenting *ACT Instant* to a customer?

- Never
- 1 – 2 times
- 3 – 4 times
- 5 – 6 times
- More than 6 times

How often have you been involved in presenting *Immerse* to a customer?

- Never
- 1 – 2 times
- 3 – 4 times
- 5 – 6 times
- More than 6 times

Figure 17 - Question type: Scale Grid



The following items involve your perception on whether an AI solution, such as *ACT Instant* and *Immerse*, would provide accurate information. In these items, a distinction has been made between *ACT Instant* and *Immerse* due to the differentiation of AI technology.

Please indicate the extent to which you agree with the following statements.

I think that the outcomes and predictions produced by *ACT Instant* are accurate

Strongly disagree 1 2 3 4 5 6 7 Strongly agree

Recommendations based on outcomes of *ACT Instant* are in general precise

Strongly disagree 1 2 3 4 5 6 7 Strongly agree

The outcomes and predictions of *ACT Instant* are ____ than survey solutions using solely human output

Far less accurate 1 2 3 4 5 6 7 Far more accurate

I think that the outcomes and predictions produced by *Immerse* are accurate

Strongly disagree 1 2 3 4 5 6 7 Strongly agree

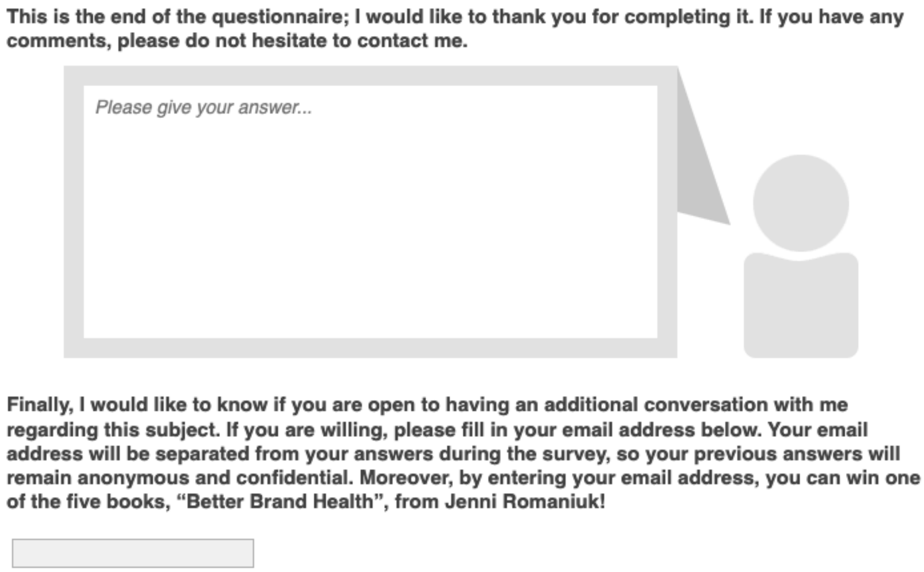
Recommendations based on outcomes of *Immerse* are in general precise

Strongly disagree 1 2 3 4 5 6 7 Strongly agree

The outcomes and predictions of *Immerse* are ____ than survey solutions using solely human output

Far less accurate 1 2 3 4 5 6 7 Far more accurate

Figure 18 - Closure of Questionnaire



This is the end of the questionnaire; I would like to thank you for completing it. If you have any comments, please do not hesitate to contact me.

Please give your answer...

Finally, I would like to know if you are open to having an additional conversation with me regarding this subject. If you are willing, please fill in your email address below. Your email address will be separated from your answers during the survey, so your previous answers will remain anonymous and confidential. Moreover, by entering your email address, you can win one of the five books, "Better Brand Health", from Jenni Romaniuk!

Appendix G

In this research Factor Analysis (FA) was used to determine if the measurement quality of the created constructs were sufficient to investigate the hypotheses. When performing an FA using the entire dataset, identifying distinct factors was challenging without deleting essential items. A limitation of FA is its assumption of linear relationships among input features; therefore, it could be less effective for datasets with items that lack linear relationships. Given that attitude, behavioural intention, and perceived accuracy were measured for two different products, ACT Instant and Immerse; the decision was made to conduct individual FAs for these items. Therefore, the data were divided into four groups, namely:

1. *AI readiness*, *awareness*, *social influence*, and *customer stewardship*.
2. *Attitude*, *behavioural intention*, and *perceived accuracy* (ACT Instant).
3. *Attitude*, *behavioural intention*, and *perceived accuracy* (Immerse).
4. *Relative advantage*, *customer knowledge*, *selling target* and *intrinsic motivation* (Exploratory variables).

Several guidelines before investigating the factors are recommended when conducting an FA to ensure reliable and validated outcomes, such as Bartlett's test of Sphericity and KMO measure of sampling adequacy. Bartlett's test produced significant results for all the items divided into the four groups. Furthermore, the KMO measures exceeded .70, suggesting that a substantial amount of shared variance exists among the variables. Therefore, it was concluded that each group was suitable for factor analysis. The intended factors of all the groups were identified using a varimax rotation. The subsequent sections will provide more details about the factor analysis process.

First, an FA was conducted on group 1: *AI readiness*, *awareness*, *social influence*, and *customer stewardship*, consisting of 21 items. Upon reviewing the communalities for all 21 items, it was observed that AIR1, AIR2, AIR5, and AIR8 fell below the cut-off point of .40. Before deleting these items, the factor loadings were examined, revealing values for these items below the threshold of .60. Deliberately, AIR1, having the lowest communality and factor loading, was eliminated first. Subsequently, the FA was performed multiple times, systematically evaluating the communalities and factor loadings, deleting one item at a time. Ultimately, AIR1, AIR2, AIR7 and AIR8 were removed from the dataset. Finally, there was a remaining set of 17 items (as depicted in Table 12). As presented in the table, factor loadings demonstrated that all measures exceeded .70, except for AIR5, which exhibited a loading of .61, which is still acceptable according to Field (2009).

Table 12 shows a notable difference within the items representing social influence, where items SI1, SI2, and SI3 load onto factor 4, while items SI4, SI5, and SI6 load onto factor 5. As social influence in this research was assessed through subjective norms and social identity, the items were also based on these two constructs. Since all these items had communalities exceeding .50 and factor loadings greater than .70 (see Table 12), separation of social influence was appropriate. Before creating these separate constructs, the reliability of subjective norms and social identity was evaluated using Cronbach's alpha. The obtained Cronbach's alphas for subjective norm and social identity exceeded the required level of .60. As a result, subjective norm and social identity will be examined as two separate constructs, both consisting of 3 items.

Table 12 - Results factor analysis for AI readiness, Awareness, Social influence, and Customer stewardship

	Customer stewardship	Awareness	AI readiness	Subjective norm	Social identity
AIR6			**.84**		
AIR4			**.79**		
AIR3			**.78**		
AIR5			**.61**		
AW1		**.93**			
AW2		**.93**			
AW3		**.91**			
SI2				**.93**	
SI1				**.86**	
SI3				**.78**	
SI5					**.82**
SI4					**.75**
SI6					**.70**
CS3	**.88**				
CS2	**.88**				
CS1	**.85**				
CS4	**.70**				

Notes: Component loadings > |.39|

Afterwards, two individual FAs were conducted to evaluate *attitude*, *behavioural intention*, and *perceived accuracy* for the ACT Instant (group 2) and Immerse solutions (group 3), each containing ten items. All communalities exceeded .50. Table 13 provides an overview of the factor loadings for ACT Instant. This table shows some noteworthy cross-loadings for ATT4AI, BI1AI, BI3AI, and PA1AI. Like Table 13, Table 14 presents an overview of the factor loadings for Immerse, highlighting high cross-loadings for BI1IM, BI3IM, and PA1IM. When an item loads on multiple factors, Field (2009) suggests that the difference between those loadings should be at least .20. However, Hair et al. (2010) argue that cross-loadings should not be greater than .60. In the case of ATT4AI, BI1AI, BI1IM and BI3IM the difference between the cross-loadings is less than .20 (see Tables 13 and 14). However, these wrong cross-loadings do not exceed .60. Given the careful interpretation of the data, items primarily load on their intended factors and their derivation from validated scales, so no items were eliminated from the analyses.

Table 13 - Results factor analysis for Attitude, Behavioural intention, and Perceived accuracy (ACT Instant)

	Attitude AI	Behavioural intention AI	Perceived accuracy AI
ATT2AI	**.86**		
ATT1AI	**.85**		
ATT3AI	**.75**		
ATT4AI	**.61**	.45	.40
BI2AI		**.85**	
BI3AI	.42	**.82**	
BI1AI	.53	**.67**	
PA3AI			**.88**
PA2AI			**.78**
PA1AI	.43		**.72**

Notes: Component loadings > |.39|

Table 14 - Results factor analysis for Attitude, Behavioural intention, and Perceived accuracy (Immerse)

	Attitude IM	Perceived accuracy IM	Behavioural intention IM
ATT2IM	**.87**		
ATT1IM	**.84**		
ATT4IM	**.76**		
ATT3IM	**.75**		
BI2IM			**.90**
BI3IM	.56		**.69**
BI1IM	.58		**.63**
PA3IM		**.87**	
PA2IM		**.79**	
PA1IM	.49	**.69**	

Notes: Component loadings > |.39|

Finally, the analysis focused on the explanatory variables: relative advantage, customer knowledge, selling target, and intrinsic motivation, containing 12 items. Every item displayed communality values that were above the .50 threshold. Table 15 demonstrates high-factor loadings grouped in the intended factors without any notable cross-loadings. Therefore, the items can be confidently grouped, as there is a clear difference between the factors, which aligns with the inherent nature of these variables.

Table 15 - Results factor analysis for Relative advantage, Customer knowledge, Selling target, and Intrinsic motivation (Explanatory variables).

	Relative advantage	Customer knowledge	Intrinsic motivation	Selling target
RA2	**.87**			
RA1	**.87**			
RA3	**.88**			
CK2		**.85**		
CK3		**.85**		
CK1		**.83**		
ST3				**.82**
ST1				**.70**
ST2				**.68**
IM2			**.80**	
IM3			**.70**	
IM1			**.69**	

Notes: Component loadings > |.39|

Appendix H

Table 16 - Independent samples test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% CI Dif.	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Dif.	SE Dif.	Lower	Upper
AIR	Equal variances assumed	.39	.53	.37	102	.35	.71	.09	.23	-.37	.54
	Equal variances not assumed			.37	82.16	.36	.71	.09	.23	-.38	.55
AW	Equal variances assumed	1.20	.28	1.78	102	.04	.08	.57	.32	-.06	1.21
	Equal variances not assumed			1.75	81.73	.04	.08	.57	.33	-.08	1.22
SN	Equal variances assumed	8.31	.00	-1.84	102	.03	.07	-.31	.17	-.65	.02
	Equal variances not assumed			-1.69	63.64	.05	.10	-.31	.18	-.68	.06
SI	Equal variances assumed	1.61	.21	-1.52	102	.07	.13	-.23	.15	-.53	.07
	Equal variances not assumed			-1.46	77.09	.07	.15	-.23	.16	-.54	.08
CS	Equal variances assumed	1.61	.21	-.78	102	.22	.44	-.14	.17	-.48	.21
	Equal variances not assumed			-.75	78.31	.23	.45	-1.4	.18	-.49	.22
ATT AI	Equal variances assumed	.36	.55	-.20	102	.42	.85	-.04	.20	-.44	.36
	Equal variances not assumed			-.19	84.49	.42	.85	-.04	.21	-.45	.37
ATT IM	Equal variances assumed	5.34	.02	-.63	102	.27	.53	-.10	.16	-.40	.21
	Equal variances not assumed			-.58	63.42	.28	.57	-.10	.17	-.43	.24
PA AI	Equal variances assumed	.00	.96	-1.26	102	.11	.21	-.24	.19	-.61	.14
	Equal variances not assumed			-1.28	93.92	.10	.20	-.24	.18	-.60	.13
PA IM	Equal variances assumed	.73	.40	.35	102	.36	.73	.06	.18	-.30	.42
	Equal variances not assumed			.34	76.13	.37	.74	.06	.19	-.31	.44
BI AI	Equal variances assumed	.28	.60	.32	102	.37	.75	.08	.25	-.42	.58
	Equal variances not assumed			.32	86.74	.37	.10	.08	.25	-.42	.58
BI IM	Equal variances assumed	1.25	.27	.01	102	.50	.75	.00	.23	-.45	.45
	Equal variances not assumed			.01	76.57	.50	.99	.00	.24	-.47	.47

RA	Equal variances assumed	.00	.99	.43	102	.30	.67	.10	.24	-.37	.57
	Equal variances not assumed			.44	96.71	.33	.66	.10	.23	-.35	.56
CK	Equal variances assumed	1.28	.26	-1.15	102	.13	.25	-.19	.17	-.52	.14
	Equal variances not assumed			-1.10	75.49	.14	.27	-.19	.17	-.54	.15
ST	Equal variances assumed	.29	.59	1.06	102	.14	.29	.25	.24	-.22	.72
	Equal variances not assumed			1.07	89.15	.14	.29	.25	.24	-.22	.72
IM	Equal variances assumed	1.13	.29	-1.31	102	.10	.19	-.26	.20	-.66	.13
	Equal variances not assumed			-1.35	96.30	.09	.18	-.26	.19	-.65	.12

Appendix I

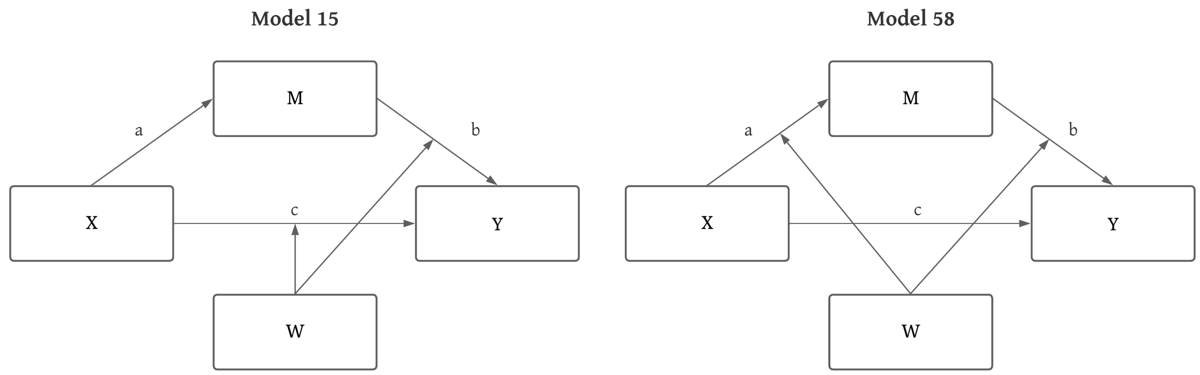
Table 17 presents an overview of the various combinations to test the conceptual model. Model 1 shows the core model's results without interaction effects. This model is used to conclude the direct effects hypotheses (H1 to H6) and to interpret the causal effects from the control variables. Models 2, 3 and 4 are used to investigate the moderating effects of customer stewardship (H7 to H9).

Table 17 - Information on different process models

	X	M	Y	W	Model
ACT Instant (AI)					
1.	Perceived accuracy AI	Attitude towards AI	Behavioural intention AI	X	4
2.	Perceived accuracy AI	Attitude towards AI	Behavioural intention AI	Customer stewardship	58
3.	Subjective norm	Attitude towards AI	Behavioural intention AI	Customer stewardship	15
4.	Social identity	Attitude towards AI	Behavioural intention AI	Customer stewardship	15
Immerse (IM)					
1.	Perceived accuracy IM	Attitude towards IM	Behavioural intention IM	X	4
2.	Perceived accuracy IM	Attitude towards IM	Behavioural intention IM	Customer stewardship	58
3.	Subjective norm	Attitude towards IM	Behavioural intention IM	Customer stewardship	15
4.	Social identity	Attitude towards IM	Behavioural intention IM	Customer stewardship	15

Table 17 highlights using two model templates for examining the hypothesised moderation effects, namely Models 15 and 58. The conceptual model hypothesised the moderation effect of customer stewardship on the relationship between perceived accuracy and attitude towards the AI solution, the relationship between social influence and behavioural intention, and the relationship between attitude towards the AI solution and behavioural intention. Hence, the decision to adopt a different template was based on the multiple interactions of customer stewardship within the conceptual model. Model 58 utilises a moderated mediation framework, with moderation applied to the a-path and b-path while excluding the c-path (or direct effect) from moderation, which would be suitable to test H7 and H9. On the other hand, Model 15 also employs a moderated mediation approach. However, moderation is applied to both the b-path and the c-path (or direct effect), which would be suitable to test H8 and H9. To visually illustrate the difference between Model 15 and Model 58, Figure 19 provides a graphical representation highlighting the variances in their respective model templates.

Figure 19 - Visual representation PROCESS Model templates 15 and 58



Appendix J

Table 18 - Linear regression results including exploratory variables

	Study 1: ACT Instant				Study 2: Immerse			
	Dependent variable				Dependent variable			
	Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards IM [b]		Behavioural intention IM [b]	
	B	t	B	t	B	t	B	t
Constant	.42	.41	**-2.53**	**-2.27**	2.57	1.84	-.62	-.50
Direct effects								
AI readiness	.09	1.25			-.09	-1.80		
Awareness	-.01	-.19			.06	1.44		
Perceived accuracy ACT Instant	**.52**	**5.36**						
Perceived accuracy Immerse					**.39**	**6.20**		
Subjective norm	**.32**	**2.66**	-.13	-.94	-.01	-.12	-.02	-.11
Social identity	.06	.54	.14	1.17	-.04	-.54	-.02	-.12
Attitude towards ACT Instant			**.77**	**7.45**				
Attitude towards Immerse							**.76**	**5.08**
Relative advantage	.04	.44	.01	.13	**.15**	**2.26**	.10	.94
Customer knowledge	.09	.76	**.32**	**2.48**	**.22**	**2.66**	.11	82
Selling target	-.03	-.50	.07	1.02	.02	.39	.05	.71
Intrinsic motivation	-.03	-.28	.10	.86	.07	.94	.02	.16
Control variable paths								
Gender: Female [c]	.18	1.09	-.18	-.96	**.25**	**2.20**	.23	1.19
Age	-.02	-1.84	.01	.46	.00	.25	-.00	-.13
Nationality: Asian Pacific [d]	-.50	-1.58	.32	.96	-.19	-.91	.10	.28
Nationality: American [d]	.04	.10	-.24	-.61	-.48	-1.90	-.34	-.80
Geographical region: AMEA [e]	.45	1.37	-.67	-1.89	.05	.23	-.07	-.18
Geographical region: LATAM [e]	-.21	-.43	**1.34**	**2.61**	**.75**	**2.21**	.84	1.53
Geographical region: NA [e]	.18	.51	.38	.97	**.55**	**2.12**	.22	.51
Department: GTIC [f]	-.08	-.27	.17	.51	.17	.85	.15	.46
Department: Research [f]	-.22	-.79	.25	.80	.20	1.06	-.18	-.54
Involvement ACT Instant	.08	.22	**.18**	**2.62**				
Involvement Immerse					**.13**	**2.59**	.14	1.62
Work experience	.08	.47	-.05	-.45	.04	.48	-.06	-.49
Sales experience	.12	1.57	-.14	-1.62	-.02	-.32	-.05	-.55
Variance explained (R^2)	61.0%		67.9%		68.5%		57.2%	

Notes:
Bold values are significant at the $p < .05$ level.
[a] AI = ACT Instant.
[b] IM = Immerse.
[c] Dummy variable: Male coded as 0, female coded as 1.
[d] Dummy variable: European coded as 0, Asian Pacific or American coded as 1.
[e] Dummy variable: Europe coded as 0, AMEA, LATAM or NA coded as 1.
[f] Dummy variable: Sales coded as 0, GTIC or Research coded as 1.

Table 19 - Regression analyses results for ACT Instant including customer knowledge

	Study 3: ACT Instant															
	Model 1 No interaction model				Model 4 Perceived accuracy				Model 2 Subjective norm				Model 3 Social identity			
	Dependent variable				Dependent variable				Dependent variable				Dependent variable			
	Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]		Attitude towards AI [a]		Behavioural intention AI [a]	
	B	t	B	t	B	t	B	t	B	t	B	t	B	t	B	t
Constant	.53	.66	-.49	-.54	**-2.71**	**-3.00**	**4.38**	**4.36**	**-3.24**	**-3.56**	**3.61**	**3.49**	**-4.69**	**-6.15**	**5.29**	**6.34**
Direct effects																
AI readiness	.10	1.38			.10	1.33			.10	1.38			.10	1.38		
Awareness	-.00	-.01			-.01	-.15			-.00	-.01			-.00	-.01		
Perceived accuracy ACT Instant	**.52**	**5.57**			**.51**	**5.32**	.01	.08	**.52**	**5.57**			**.52**	**5.57**		
Subjective norm	**.32**	**2.78**	-.13	-.92	**.32**	**2.67**	-.13	-.98	**.32**	**2.78**	-.13	-1.04	**.32**	**2.78**	-.12	-.90
Social identity	.07	.66	.20	1.66	.06	.55	.15	1.21	.07	.66	.15	1.28	.07	.66	.15	1.33
Attitude towards ACT Instant			**.80**	**7.55**			**.79**	**6.60**			**.79**	**7.76**			**.80**	**7.94**
Relative advantage	.04	.43			.04	.38			.04	.43			.04	.43		
Customer knowledge					.08	.63	**.41**	**3.24**			**.41**	**3.25**			**.38**	**3.10**
Moderating effects																
Perceived accuracy AI [a] * Customer knowledge					-.01	-.14										
Subjective norm * Customer knowledge											-.05	-.43				
Social identity * Customer knowledge															-.23	-1.77
Attitude ACT Instant * Customer knowledge							**.18**	**2.21**			**.21**	**2.02**			**.25**	**2.80**
Control variable paths																
Gender: Female [b]	.18	1.12	-.21	-1.11	.18	1.07	-.13	-.77	.18	1.12	-.14	-.76	.18	1.12	-.16	-.89
Age	**-.03**	**-2.23**	-.00	-.10	-.02	-1.89	.00	.25	**-.03**	**-2.23**	.00	.27	**-.03**	**-2.23**	.00	.16
Nationality: Asian Pacific [c]	-.44	-1.51	.32	.96	-.46	-1.55	.13	.41	-.44	-1.51	.13	.42	-.44	-1.51	.17	.56
Nationality: American [c]	.11	.33	-.13	-.33	.07	.20	-.43	-.1.14	.11	.33	-.43	-1.14	.11	.33	-.45	-1.20
Geographical region: AMEA [d]	.39	1.26	**-.81**	**-2.32**	.43	1.35	-.54	-1.55	.39	1.26	-.54	-1.59	.39	1.26	-.56	-1.68
Geographical region: LATAM [d]	-.24	-.50	**1.35**	**2.52**	-.23	-.48	**1.47**	**2.90**	-.24	-.50	**1.49**	**2.93**	-.24	-.50	**1.39**	**2.77**
Geographical region: NA [d]	.12	.35	.21	.54	.16	.45	.61	1.55	.12	.35	.61	1.57	.12	.35	.59	1.55
Department: GTIC [e]	-.11	-.39	.05	.16	-.09	-.29	.16	.51	-.11	-.39	.18	.57	-.11	-.39	.19	.61
Department: Research [e]	-.24	-1.07	-.10	-.39	-.18	-.76	.01	.02	-.24	-1.07	.00	.01	-.24	-1.07	.00	.01
Involvement ACT Instant	.08	1.24	**.19**	**2.74**	.08	1.24	**.17**	**2.56**	.08	1.24	**.17**	**2.59**	.08	1.24	**.16**	**2.47**
Work experience	.09	.85	-.03	-.23	.08	.76	-.05	-.40	.09	.85	-.05	-.46	.09	.85	-.06	-.48
Sales experience	.13	1.82	-.14	-1.62	.13	1.73	**-.17**	**-2.06**	.13	1.82	**-.17**	**-2.08**	.13	1.82	**-.16**	**-1.96**
Variance explained (R^2)	60.7%		64.1%		60.9%		69.0%		60.7%		69.1%		60.7%		70.1%	

Notes:

Bold values are significant at the $p < .05$ level.

[a] AI = ACT Instant.

[b] Dummy variable: Male coded as 0, female coded as 1.

[c] Dummy variable: European coded as 0, Asian Pacific or American coded as 1.

[d] Dummy variable: Europe coded as 0, AMEA, LATAM or NA coded as 1.

[e] Dummy variable: Sales coded as 0, GTIC or Research coded as 1.

Table 20 - Regression analyses results for Immerse including customer knowledge

	Study 4: Immerse															
	Model 1 No interaction model				Model 4 Perceived accuracy				Model 2 Subjective norm				Model 3 Social identity			
	Dependent variable				Dependent variable				Dependent variable				Dependent variable			
	Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]		Attitude towards IM [a]		Behavioural intention IM [a]	
	B	t	B	t	B	t	B	t	B	t	B	t	B	t	B	t
Constant	**2.59**	**4.04**	-.03	-.03	**-1.35**	**-2.48**	**5.22**	**5.14**	**-3.88**	**-5.28**	**5.03**	**4.60**	**-3.82**	**-6.26**	**5.01**	**5.34**
Direct effects																
AI readiness	-.09	-1.67			**-.13**	**-2.91**			-.09	-1.67			-.09	-1.67		
Awareness	**.09**	**2.07**			.07	1.92			**.09**	**2.07**			**.09**	**2.07**		
Perceived accuracy Immerse	**.41**	**6.19**			**.35**	**5.92**	.10	.78	**.41**	**6.19**			**.41**	**6.19**		
Subjective norm	-.00	-.03	-.01	-.10	-.01	-.12	-.04	-.25	-.00	-.03	.01	.08	-.00	-.03	-.02	-.17
Social identity	.01	.09	.01	.10	-.03	-.42	-.02	-.17	.01	.09	-.01	-.05	.01	.09	-.01	-.09
Attitude towards Immerse			**.80**	**5.75**			**.70**	**3.66**			**.73**	**4.48**			**.74**	**4.40**
Relative advantage	**.07**	**2.88**			**.18**	**3.03**			**.07**	**2.88**			**.07**	**2.88**		
Customer knowledge					**.16**	**2.19**	.15	1.08			.15	1.08			.16	1.15
Moderating effects																
Perceived accuracy IM [a] * Customer knowledge					**-.22**	**-3.97**										
Subjective norm * Customer knowledge											.19	1.65				
Social identity * Customer knowledge															.15	1.10
Attitude Immerse * Customer knowledge							.03	.33			-.05	-.46			-.02	-.20
Control variable paths																
Gender: Female [b]	**.26**	**2.20**	.20	1.06	**.28**	**2.73**	.23	1.20	**.26**	**2.20**	.24	1.27	**.26**	**2.20**	.25	1.30
Age	-.00	-.40	-.00	-.27	.00	.59	.00	.02	-.00	-.40	-.00	-.07	-.00	-.40	.00	.01
Nationality: Asian Pacific [c]	-.18	-.86	.12	.35	-.23	-1.23	.06	.19	-.18	-.86	.06	.18	-.18	-.86	.02	.05
Nationality: American [c]	-.38	-1.49	-.27	-.67	-.43	-1.89	-.39	-.94	-.38	-1.49	-.41	-1.00	-.38	-1.49	-.38	-.92
Geographical region: AMEA [d]	-.05	-.25	-.13	-.38	.02	.12	-.07	-.19	-.05	-.25	-.09	-.26	-.05	-.25	-.04	-.11
Geographical region: LATAM [d]	**.73**	**2.07**	.81	1.48	**.83**	**2.67**	.84	1.52	**.73**	**2.07**	.84	1.54	**.73**	**2.07**	.94	1.69
Geographical region: NA [d]	.43	1.69	.13	.31	.43	1.83	.26	.61	.43	1.69	.27	.64	.43	1.69	.27	.64
Department: GTIC [e]	.06	.32	.12	.39	.10	.56	.21	.63	.06	.32	.10	.29	.06	.32	.14	.43
Department: Research [e]	-.04	-.23	-.27	-1.01	.18	1.17	-.16	-.55	-.04	-.23	-.21	-.66	-.04	-.23	-.21	-.75
Involvement Immerse	**.12**	**2.38**	.13	1.57	**.12**	**2.62**	.14	1.71	**.12**	**2.38**	.13	1.57	**.12**	**2.38**	.14	-1.70
Work experience	.05	.66	-.05	-.44	.05	.70	-.07	-.55	.05	.66	-.03	-.23	.05	.66	-.06	-.45
Sales experience	-.01	-.19	-.05	-.59	-.03	-.70	-.07	-.74	-.01	-.19	-.08	-.93	-.01	-.19	-.08	-.86
Variance explained (R^2)	64.6%		56.4%		73.2%		57.2%		64.6%		58.3%		64.6%		57.5%	

Notes:
Bold values are significant at the $p < .05$ level.
[a] IM = Immerse.
[b] Dummy variable: Male coded as 0, female coded as 1.
[c] Dummy variable: European coded as 0, Asian Pacific or American coded as 1.
[d] Dummy variable: Europe coded as 0, AMEA, LATAM or NA coded as 1.
[e] Dummy variable: Sales coded as 0, GTIC or Research coded as 1.