Hybrid Human-AI Consulting Models in Insurance: Effects on Trust, Transparency, and Customer Loyalty in Generation Z

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Abstract – Português

Título: Modelos híbridos de consultoria humana-IA em seguros: efeitos na confiança, transparência e fidelidade do cliente na Geração Z

Palavras-chave: Consultoria em seguros, Geração Z, Inteligência Artificial, Confiança, Transparência, Processos digitais, Fidelidade do cliente, Aceitação da IA, Interação humana-IA, Experiência do cliente, Retenção do cliente

Introdução: Este estudo examina como a Geração Z percebe três modalidades de aconselhamento em seguros: humano, exclusivamente baseado em IA e híbrido, e como essas percepções influenciam confiança, transparência, atribuição de responsabilidade e fidelização. O estudo insere-se na crescente integração da IA em setores intensivos em aconselhamento e nas expectativas da Geração Z quanto a processos digitais eficientes aliados à responsabilização humana.

Método: Num estudo transversal, 84 participantes da Geração Z responderam a um questionário online e foram alocados aleatoriamente a um de três cenários de aconselhamento. Confiança, transparência, responsabilidade, fidelização e atitudes em relação à IA foram mensuradas por escalas Likert de 7 pontos. Os dados foram analisados por estatísticas descritivas, correlações bivariadas, testes t, ANOVA e regressões múltiplas.

Resultados: Os resultados indicam diferenças significativas entre os cenários. O aconselhamento exclusivamente apoiado em IA recebeu as avaliações mais críticas, sobretudo em transparência e responsabilidade. O modelo híbrido apresentou os valores mais elevados nessas dimensões, com níveis de confiança comparáveis ao aconselhamento humano. As regressões mostraram que confiança e atribuição de responsabilidade são preditores centrais da fidelização, enquanto a transparência influencia a lealdade indiretamente por meio dessas variáveis. Uma atitude positiva em relação à IA não se traduziu em maior aceitação de decisões exclusivamente automatizadas.

Discussão: Conclui-se que a Geração Z aceita consultoria com IA quando há recomendações compreensíveis e responsabilidade clara, não pela IA. IA isolada gera “caixa-preta” e lacuna; o híbrido aumenta transparência. Sem diferenças de confiança, use explicabilidade e supervisão humana para lealdade.

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Abstract – English

Titel: Hybrid Human-AI Consulting Models in Insurance: Effects on Trust, Transparency, and Customer Loyalty in Generation Z

Keywords: Insurance advice, Generation Z, Artificial Intelligence, Trust, Transparency, Digital processes, Customer loyalty, Acceptance of AI, Human-AI Interaction, Customer Experience, Customer retention

Introduction: This study explores how Gen Z perceives three types of insurance advice: human, purely AI-based, and hybrid. It also examines how these perceptions affect trust, transparency, attribution of responsibility, and customer loyalty. The context for this research is the growing integration of AI in advice-intensive industries and Generation Z's specific expectations regarding digital processes and human accountability.

Method: In a cross-sectional study, 84 members of Gen Z completed an online survey, randomly assigned to one of three consulting scenarios. Trust, transparency, responsibility, loyalty, and attitudes toward AI were measured using 7-point Likert scales. The analysis was conducted using descriptive statistics, bivariate correlations, t-tests, ANOVA, and multiple regressions.

Results: Findings reveal significant differences across scenarios. Purely AI-based advice received the most critical ratings, particularly for transparency and responsibility. Hybrid advice achieved the highest scores in both areas and trust levels comparable to human advice. Regression analysis revealed that trust and attribution of responsibility are key predictors of customer loyalty, while transparency impacts loyalty indirectly through these variables. Interestingly, a generally positive attitude toward AI did not result in greater acceptance of AI-based decisions.

Discussion: The results suggest that Generation Z’s acceptance of AI-supported insurance advice depends mainly on understandable recommendations and clear responsibility, rather than AI alone. The AI-only condition creates black-box impressions and a responsibility gap, whereas hybrid formats improve transparency and accountability through human mediation. As trust differences are not significant, insurers should focus on consistent explainability and visible human oversight to build long-term loyalty.

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Table of Contents

Table of Figures

Index of Tables

Table of Abbreviation

AI ..... Artificial Intelligence
ANOVA ..... Analysis of Variance
EIOPA ..... European Insurance and Occupational Pension Authority
GDPR ..... General Data Protection Regulation
Gen Z ..... Generation Z
M ..... Mean / Average
n ..... Sample size / Number of observations
R^2 ..... Coefficient of determination
SD ..... Standard deviation
SPSS ..... Statistical Package for the Social Sciences
TAM ..... Technology Acceptance Model
UTAUT ..... Unified Theory of Acceptance and Use of Technology
XAI ..... Explainable Artificial Intelligence

1 Introduction

1.1 Problem definition and objective of the thesis

The insurance industry is currently experiencing major changes. Customers increasingly expect to research, compare, and even complete insurance products online, while insurers are under pressure to redesign distribution processes and customer touchpoints accordingly (Candreia et al., 2024). Concurrently, digital transformation in insurance is increasingly driven by Insurtech applications, including Artificial Intelligence (AI)- and data-based solutions that reshape business processes, distribution channels and the development of new insurance services (Holland & Kavuri, 2025). At the same time, the insurance context is particularly sensitive because insurance policies are not "tangible" products whose benefits are immediately apparent. They are intangible services whose value often only becomes apparent later, for example, in the event of a claim or benefit payment. As a result, many decisions are based less on product quality that can be verified in the short term and more on trust, perceived competence, and the quality of advice (Eickenberg, 2022). In practice, this means that the more complex the product and the greater the financial consequences of a wrong decision, the more important transparency, fairness, and accountability become. These requirements are becoming even more important as a result of digitalization, because decision-making processes are becoming more data-driven and customers are increasingly asking themselves how recommendations are made and who is responsible for them (EIOPA, 2024). At the same time, insurance companies are increasingly using AI-based recommendation systems to digitize risk assessment, pricing, and customer interaction (McKinsey, 2025). Within this development, Generation Z is becoming particularly relevant for insurers from a strategic perspective.

On the one hand, the market is changing: long-term growth depends less on generating additional sales to older target groups and more on acquiring new customers at an early stage and retaining them in the long term. Gen Z is at the beginning of its insurance biography, taking out policies independently for the first time and repeatedly adjusting insurance decisions throughout its life course, for example, when pursuing education, changing jobs, moving, or starting a family. This makes Gen Z interesting for insurers not only in the short term, but above all as a target group for long-term customer relationships (Dennstedt & Targan, 2025; Gerhardus, 2023b). On the other hand, the expectations of this target group differ significantly from those of traditional consulting clients. Gen Z has grown up with digital services and expects processes that are fast, mobile, and intuitive. As digital natives, they expect services that are as "ready to consume" as possible, digitally accessible, and require minimal effort to

engage with while at the same time attaching great importance to transparency, ethical conduct, and clear responsibility (Gerhardus, 2021). For insurers, this means that anyone who wants to win over this target group must design their advisory services in such a way that they enable digital orientation while at the same time conveying security, control options, and clear responsibilities (Dennstedt & Targan, 2025; Gerhardus, 2023b; McKinsey, 2025).

The aim of this master's thesis is therefore to systematically compare the perception of three consulting formats in the insurance context: purely human consulting, purely AI-based consulting, and hybrid consulting (human contact person plus AI support). Transparency/comprehensibility, attribution of responsibility, trust, and loyalty intentions are examined. The paper is structured in such a way that the state of research and theoretical foundations are presented first, followed by methodology and study design, then the results are presented and discussed, and finally strategic recommendations for action are derived.

1.2 Scope of the thesis

This master's thesis focuses exclusively on Gen Z's perception of three specific forms of advice-human, AI-based, and hybrid - and their influence on trust, transparency, attribution of responsibility, and customer loyalty. Due to the limited scope of this thesis, it is not possible to cover all aspects of digital transformation in the insurance industry in detail. An important limitation in terms of content is that the thesis considers insurance as a general category. No distinction is made between different types of insurance. This serves to reduce complexity and enables a uniform analysis of the forms of advice. A differentiated consideration of insurance types would clearly exceed the scope of this work and impair the comparability of the scenarios. In addition, the work focuses exclusively on perceived constructs such as trust, transparency, fairness, and attribution of responsibility, but not on objective performance indicators or actual decision-making behavior. A qualitative deepening is also deliberately not undertaken, as the aim of the work is to quantitatively compare the three forms of advice.

2 Current state of research and theoretical foundations

2.1 Theoretical classification of human, AI-based and hybrid consulting

Research distinguishes between three basic consulting models in the insurance environment, which differ not only technically, but above all in terms of the social processes through which trust, transparency, and attribution of responsibility arise. Traditional human consulting refers to an interpersonal, face-to-face service process in which a consultant gathers information, analyses the individual situation, makes recommendations and, from the customer's perspective, bears the central responsibility for these recommendations (Morgan & Hunt, 1994). AI-based consulting, on the other hand, describes largely automated, algorithmic recommendation systems that process customer data, create risk profiles, and generate suggestions without direct interaction with a human consultant (Kern & Loh, 2024; Zarifis et al., 2019). Finally, hybrid advice can be understood as a human-in-the-loop approach: AI systems perform preliminary analyses and generate initial recommendations, which are then reviewed, contextualized and discussed with the customer by a human advisor. The final recommendation and its responsibility thus remain with the human, while the AI serves as a supporting decision system (Do Khac & Leyer, 2025; Rieger et al., 2025).

2.2 Change in the insurance industry

Insurance consulting has traditionally been characterized by personal proximity and long-term customer relationships (Insurance Industry, 2023). However, with Gen Z entering the market and digital technologies becoming embedded in business processes, advisory structures increasingly shift towards multi-channel, data-based and algorithmically supported formats (Gerhardus, 2023a; Hersch et al., 2022). This change is not only technical but also cultural: policyholders today expect transparency, control and individualization, values that are particularly pronounced among Gen Z (Merriman et al., 2023; Rapp & Réthy-Jensen, 2023). The study of Dennstedt & Targan (2025) shows that Gen Z, as “digital natives”, generally views automation positively but is skeptical of algorithmic decisions when their functioning is not explained in a comprehensible manner. This is consistent with the findings of Kern & Loh (2024), which emphasize that trustworthy AI in insurance must be explainable, controllable and verifiable. According to Gerhardus (2023b), consulting and sales are therefore likely to be dominated by hybrid models in the coming years. While AI systems efficiently evaluate datasets

and recognize patterns, human consultation remains crucial to ensure trust, empathy and situational judgement (Witt & Schissler, n.d.).

2.3 Trust, fairness and transparency

Trust has always been the basis of insurance relationships (Mayer et al., 2007). However, with the advance of digitalization, the meaning of trust is changing. Instead of trusting mainly human advisors, people are increasingly placing their trust in algorithmic systems (Miller, 2025). In this context, research on trust in algorithmic systems has identified two central mechanisms. Algorithm aversion describes the tendency to distrust algorithms after they have made visible mistakes, even if they are statistically more accurate than humans (Dietvorst et al., 2014). In contrast, algorithm appreciation refers to the tendency to prefer algorithmic decisions when they are perceived as understandable, explainable and objective (Logg et al., 2019). In the insurance environment, this means that customers are more willing to trust AI systems if they understand how decisions are made and if they feel their individual circumstances have been considered (van der Hulst et al., 2023). Building on this, empirical studies emphasize explainability. Shin (2021) confirms that "explainable AI" (XAI), significantly strengthens the perception of fairness and trust, as it reduces uncertainty and makes the decision appear rational and verifiable. Similarly, the Kern & Loh paper (2024) formulates this finding as a technical and ethical guideline. Only systems that are traceable and auditable can survive in highly regulated markets such as insurance. In addition to its link to trust, perceived fairness plays an independent role. Zarifis et al. (2019) show that perceived fairness is a key driver of satisfaction and loyalty. If customers get the impression that AI systems are unfair or discriminatory, trust immediately declines, even if the decision's objective quality is high. This finding is confirmed by Kacperska et al. (2024), who show that Gen Z is particularly sensitive to ethical issues and prefers hybrid models because they combine algorithmic neutrality with human control. Ultimately, trust, fairness and transparency form an interdependent system. Transparency increases the perception of fairness, fairness strengthens trust, and trust leads to loyalty. Based on this, some authors point to hybrid consulting models. In these models, AI provides the data-driven analysis, while a human advisor explains the result and takes responsibility for the final recommendation (Gerhardus, 2023b; Miller, 2025).

2.4 Generation Z

While earlier generations often perceived digitalization as an unequivocal sign of progress, Gen Z can be characterized by a more ambivalent relationship towards it (Gerhardus et al., 2024). This generation uses digital technologies as a matter of course, yet at the same time expect high levels of transparency, ethical standards, and opportunities for participation and co-creation (Abels, 2025; Rapp & Réthy-Jensen, 2023). Thus, in contrast to older generations, their trust is based less on long-term brand loyalty and more on perceived behavioral authenticity. Companies are therefore required to demonstrate consistently that they act in an ethical, sustainable and transparent manner (Dennstedt & Targan, 2025; Michelle, 2025). According to Gerhardus (2023b), Gen Z wants advice that it perceives as "supportive, not patronizing" (Gerhardus, 2023b). It expects insurers to use digital tools to simplify processes, but also to involve human contact persons to explain complexities. The Signal Iduna study (2025) adds that trust in insurers is primarily built through attitude and explainability, not product diversity. Furthermore, Gaedeke (2024) emphasizes that Gen Z has a strong need for control and accepts data-driven decisions only if it is comprehensible. These requirements are also reflected in the Miller (2025) study. 71% of Gen Z respondents report they accept data-based insurance decisions only if they understand how their data is used. Thus, trust in insurers for Gen Z is not only shaped by reputation but increasingly by data ethics, communication quality and human involvement (Miller, 2025).

2.5 Technology acceptance and regulatory context

The acceptance of digital technologies is often described with the Technology Acceptance Model (TAM) (Davis, 1987) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Both models assume that people mainly use technology when they perceive it as valuable and easy to use. In the context of AI-based insurance consulting a further factor is central: trust in the technology (Kern & Loh, 2024). The Kern & Loh white paper (2024) describes this aspect as a necessary condition for "trustworthy AI". AI systems must be designed so that they do not replace human control but rather enhance it. Hacker & Eber (2025) also refers to the EU AI Act, which requires insurers to demonstrate that the AI systems they use are explainable, fair and non-discriminatory. Capraro (2024) asserts that technical safeguards must be paired with transparent and ethical communication. Users trust AI when they see it as a helpful tool instead of perceiving it as a system that makes unclear decisions about them. In combination with TAM and UTAUT, this provides a conceptual basis

for consulting formats in which AI-based analysis is combined with clear human oversight: AI can increase efficiency and ease of use, while human interaction and transparent explanation foster trust in the technology.

2.6 Customer loyalty

In the insurance industry, customer loyalty is closely linked to trust, satisfaction and perceived fairness (Bughin et al., 2017). It is not the result of short-term customer experiences, but rather a consistent chain of trust that extends from data usage to consulting to claims settlement. McKinsey (2025) emphasizes that loyalty in the digital environment can only be achieved by combining efficiency, transparency and empathy. Gerhardus (2023b) and Dennstedt & Targan (2025) add that companies that credibly combine people and technology achieve higher recommendation rates. In the context of Gen Z, loyalty is increasingly defined by values: ethics, sustainability and transparent communication have a stronger impact than price or product range (Abels, 2025; Rapp & Réthy-Jensen, 2023). Loyalty thus functions not only as an economic concept, but also as a social and moral concept of commitment that requires trust and fairness (Ali et al., 2025).

3 Methodology

This master's thesis examines how hybrid human-AI consulting models in the insurance sector influence the trust, perceived transparency, and customer loyalty of Gen Z. A quantitative study design was chosen because the research questions aim to systematically compare different consulting formats (see Table 1) and statistically test theoretically derived hypotheses. Quantitative methods make it possible to reliably measure differences in mean values and correlations between variables and to evaluate them using standardized scales. Moreover, a quantitative approach is particularly appropriate, as capturing variation in perceptions within Gen Z requires a sufficiently large sample. Qualitative interviews could provide deeper insights into individual decision progresses, but they would not allow for generalizable statements about differences between three consulting formats or the testing of hypotheses. The quantitative design therefore offers a suitable balance between ecological validity (through realistic scenarios) and statistical generalizability (through a broader sample size). To answer the research question, a quantitative online experiment was implemented. Online surveys are well suited to Gen Z, who prefer digital, mobile formats and show high response rates in online environments (Mangal et al., 2023). The survey was conducted independently, anonymously and in compliance with the General Data Protection Regulation (GDPR). The methodological approach is based on the recommendations of Döring & Bortz (2016), Cohen (2009) and Backhaus et al. (2021) for quantitative research designs. The study uses a cross-sectional design with three independent groups, each representing a different consulting model in the insurance context. A cross-sectional design is appropriate because the study focuses on participants' immediate evaluations rather than long-term behavioral developments. To ensure comparability across groups, an experimental vignette design (scenarios: Table 1) was used to manipulate the advisory formats while keeping the conditions highly comparable across participants. It also minimizes interviewer effects and ensures consistent stimulus presentation across participants (Stockemer & Bordeleau, 2023).

Group	***Example Items***	***Sources***
Human-only	Advice provided exclusively by a human insurance advisor.	Dietvorst et al. (2015); Logg et al. (2019)
AI-only	Advice provided exclusively by an AI system that makes the decision completely automatically.	Dietvorst et al. (2015); Logg et al. (2019)
Hybrid	Combination of AI analysis and human review, explanation and adjustment of the recommendation.	Cambon et al. (2022); BearingPoint (2023a, 2023b)

Table 1: The three different consulting models in insurance[1]

After reading the scenario, participants rated their perceptions of the consulting interaction on 7-point Likert scales *(1 = strongly disagree, 7 = strongly agree).* The study builds on experimental work on algorithm aversion and algorithm appreciation (Dietvorst et al., 2014; Logg et al., 2019) and transfers this approach to hybrid human-AI interaction in the insurance context (Kern & Loh, 2024). Using validated Likert scales allows to quantitatively capture latent constructs such as trust and perceived transparency with sufficient reliability (Stockemer & Bordeleau, 2023). However, this method also has important limitations: cross-sectional data cannot capture temporal dynamics or the stability of causal effects, self-report measures may be influenced by social desirability, and scenario-based studies cannot fully reproduce the emotional and relational complexity of real consulting encounters. These limitations are discussed in more detail in chapter 7.

[1] Own representation.

3.1 Deriving the hypothesis

The hypotheses of this study are derived directly from the theoretical framework in chapter 2. This framework highlights trust, perceived fairness and transparency, responsibility attribution, customer loyalty, attitudes toward AI, and acceptance of AI decisions as central psychological variables in human-AI interactions in the insurance context. Prior research suggests that human involvement can strengthen perceptions of fairness and responsibility (Do Khac & Leyer, 2025; Miller, 2025), whereas algorithmic systems may create uncertainty when their decision-making is not explainable (Kern & Loh, 2024). Trust is particularly relevant because insurance is an intangible service and trustworthiness is often inferred from the advisory situation (van der Hulst et al., 2023). Fairness and transparency shape whether recommendations are perceived as legitimate and understandable, which is especially important for Gen Z. Responsibility attribution was included because unclear accountability can reduce acceptance of algorithmic decisions (Zhou et al., 2021). Loyalty serves as the key outcome variable, as insurers increasingly depend on long-term, trust-based relationships (Minta, 2025). Finally, attitudes toward AI were considered because general AI perceptions can influence willingness to accept AI-supported recommendations (Pal et al., 2023). Together, these variables provide a theoretically grounded basis for examining hybrid advisory formats. Based on this, the following hypotheses were formulated (see Figure 1).

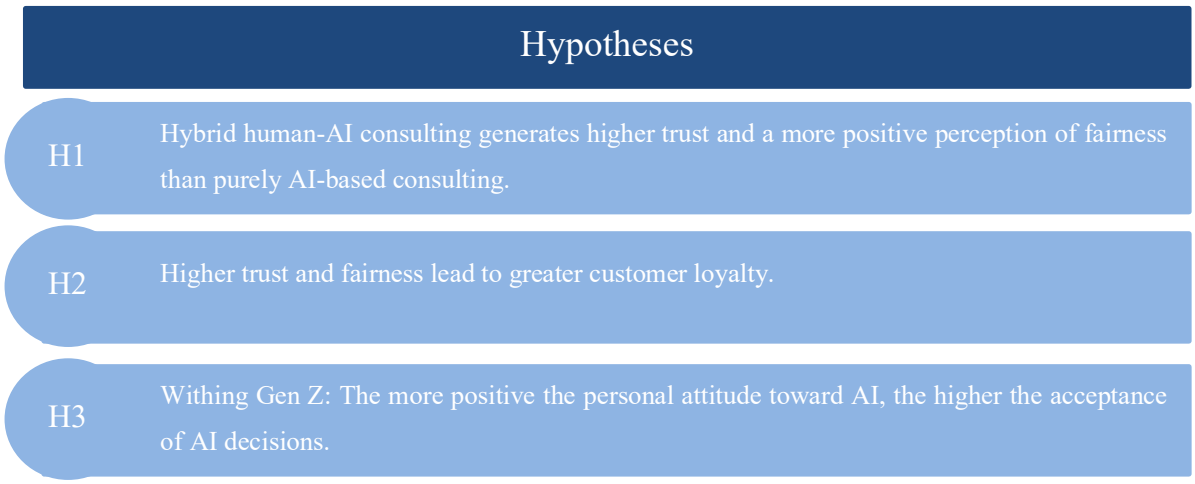

Figure 1: Hypotheses presentation[2]

The theoretical derivation therefore informs not only the hypotheses but also the selection of variables, measurement instruments, and analytical strategies.

[2] Own representation.

3.2 Data collection procedure

The data were collected through an online questionnaire, which is an established and efficient method for capturing subjective evaluations in a standardized format. Online surveys offer anonymity, reduce interviewer bias, and enable participants to respond at their convenience. These characteristics are advantageous in research on trust and technology perception, where social desirability may otherwise influence responses (Döring & Bortz, 2016).

3.2.1 Random sample

Participants were recruited via social media and snowball sampling. This sampling strategy was selected because Gen Z is highly active on social media, making platforms like Instagram an effective access point for reaching this demographic with minimal recruitment barriers. A probabilistic sampling method was not feasible due to resource constraints and typically yields lower response rates for young digital-native populations. Recruitment took place via social media published on my personal profile on October 20, 2025, at 3:15 p.m. (reach: 1,142 followers, of whom approx. 530 were active viewers) and was expanded using a snowball sampling method via friends and family networks. The online survey was activated between October 20 and 25, 2025. The study group consists of members of Gen Z aged 13 to 28. This sampling approach is appropriate for exploratory research but limits the generalizability of the findings, as participants may not be representative of the broader German Gen Z population.

3.2.2 Questionnaire

The online questionnaire was developed based on theoretical concepts and existing, empirically validated scales. The structure follows the format of a quantitative questionnaire: *an introduction, a main section and conclusion.*

The introductory section briefly explains the aim of the study, followed by information on anonymity, data protection (GDPR) and the approximate duration of the survey.

The main part consists of six topics and includes three test scenarios, randomly assigned to participants. The first scenario is human-only, the second one is AI-only, and the third one is hybrid (human-AI). Following the respective consulting scenario, perceived transparency is measured using questions about how the recommended contract design is arrived at, how clear and transparent the advice is, how well the underlying data and criteria are explained, and how

appropriate the recommendation appeared. In addition, the provider's transparent communication is evaluated (impression of responsible handling of personal data, openness in the transfer of information, comprehensibility of the recommendation, and compliant and responsible use of new technologies such as AI). This is followed by an evaluation of responsibility, including how clearly the responsible party for the final recommendation is identified, how confident participants felt about a responsible person being involved, and how appropriate the distribution of responsibility is perceived. In the trust section, three subscales are used based on the scenarios: trust in advisors, including perceived expertise, acting in the customer's interest, honesty and reliability. Trust in AI, which included the objectivity and accuracy of recommendations, reliability and expected fairness and trust in the insurance company, which included general trust in the company, the responsible use of AI, adequate employee training for sound recommendation practices, and the impression of ethical, moral and transparent conduct. In the human-only scenario, only trust in advisors is measured, in the AI-only scenario, only trust in AI is measured and in the hybrid scenario, both trust in advisors and trust in AI are assessed.

In the final section, participants are asked about their demographic background, including age, gender and level of education, as well as two screening questions about whether they already hold an insurance policy and whether they have experience with AI-based tools (Equation 1).

3.2.3 Data analysis

The statistical analysis proceeded in two stages. Descriptive statistics provided an initial overview of the sample and the main variables, while inferential analyses enabled hypothesis testing.

Descriptive statistics

After completing the online survey, the data were exported from the survey tool as a CSV file, initially organized into tables in Microsoft Excel, and then further processed in IBM SPSS Statistics, version 27.0.1.0. Before conducting any analyses, systematic data cleaning was performed: variable names and value labels were standardized, obvious typing or coding errors were corrected, and missing values were marked as *system missing or defined user missing*. Only completed questionnaires were included in the analysis (initial N = 104, after cleaning N = 84). Cases were assigned to the intended consulting scenarios (human, AI-only, hybrid) and this assignment was checked using manipulation/control questions. If respondents did not

clearly assign the described situation to one of the three formats or left the corresponding control question unanswered, these cases were stored in SPSS as a separate category ("no clear assignment"). This category does not represent an additional consulting scenario. It is used to document unclear scenario recognition and, where applicable, to provide a robustness-oriented overall comparison. Missing responses were treated item by item (pairwise deletion). Therefore, the reported case numbers (n) vary across items and indices. The descriptive analysis included the mean value (M), standard deviation (SD), and sample size (n), for categorical characteristics (e.g., gender, educational attainment), absolute and relative frequencies were reported. Minimum and maximum values were not reported for Likert items, as the theoretically possible range is consistently 1 to 7.

Inference statistics

For the inference statistics, data quality and test assumptions were checked first and regarding the interpretation guidelines (see Table 2) assumpt. Internal consistency of the multi-item scale was assessed using Cronbach's α, with $\alpha \geq .70$ as the minimum criterion. Variance homogeneity between groups was examined with Leven's test. Where this assumption was violated, Welch corrections with adjusted degrees of freedom were applied. The significance level for all tests was set at $\alpha = .05$. Where there was clear directional expectation (e.g., positive correlations), one-sided p-values were reported; otherwise, two-sided p-values were reported. Negatively polarized items, if any, were recoded so that higher values always meant a higher expression of the respective construct. If p is smaller than the probability of error α, the null hypothesis is rejected (Sill, 2022).

In addition to p-values, effect sizes are specified and interpreted:

Statistical tests	Metric	Small	Medium	Large
t-test	Cohen's d	$d \approx 0.20$	$d \approx 0.50$	$d \approx 0.80$
ANOVA	Partial η^2_p	$\eta^2_p \approx 0.01$	$\eta^2_p \approx 0.06$	$\eta^2_p \approx 0.14$
Regression/ Correlation	Standardized β weights	Varies, often interpreted alongside	Varies, often interpreted alongside	Varies, often interpreted alongside
	R^2 (explained variance)	Varies, use relative to the context and other variables	Varies, use relative to the context and other variables	Varies, use relative to the context and other variables

Table 2: Interpretation guidelines[3]

Depending on the question and scale level, different statistical methods were used to validate the hypotheses.

> *H1: Hybrid human-AI consulting generates greater trust, a more positive perception of fairness and transparency, and clearer attribution of responsibility than pure AI consulting.*

Hypothesis 1 is primarily examined through planned group comparisons between the AI-only (scenario 2) and the hybrid condition (scenario 3), because the hypothesis is directional and targets the added value of human involvement compared to pure automation. To contextualize the results across formats, additional omnibus comparisons were conducted. In most cases, this overview is based on the three intended scenarios (human vs. AI-only vs. hybrid). In some analyses, SPSS also contains a small additional category labelled as “no clear assignment”, which reflects respondents who did not clearly recognize or assign the scenario in the manipulation/control check. Where this category is included in an ANOVA, the resulting test

[3] Own representation based on (SPSS TUTORIALS, n.d.).

refers to a four-group comparison and serves as an additional robustness-oriented indication of the overall pattern rather than as evidence for a fourth consulting format.

> *H2: Greater trust and more positive perceptions of transparency/fairness and accountability lead to greater customer loyalty toward the insurance provider.*

This hypothesis was tested using multiple linear regression, with loyalty as the dependent variable and the three psychological constructs entered simultaneously as predictors. All respondents were included in this analysis, regardless of the scenario to which they had been assigned, because the hypotheses address general relationship between these variables rather than specific formats differences.

> *H3: Within Gen Z: The more positive the personal attitude toward AI is, the higher the acceptance of AI decisions.*

Here, multiple linear regression was again used, with AI attitude as the independent variable. The analysis was restricted to participants in the AI-only and hybrid scenarios, as only these groups answered the AI-acceptance items. The detailed numerical results of these analyses are reported in chapter 4.

4 Results

This chapter presents the results of the quantitative survey conducted for this study. First, the sample (n=84), divided into three consulting scenarios, is described to provide an overview of the participants and their key demographic and descriptive characteristics. The results are then presented in relation to the three consulting scenarios, human consulting, AI-supported consulting and hybrid consulting. In particular, the focus is on how the participants responded to the respective questions in each scenario. For each item, the mean (M), standard deviation (SD) and the number of responses evaluated (n) are reported. Lower case numbers for individual items are due to missing responses. For individual items, only two valid responses are available (n = 2); these values are reported, but their significance is limited.

Description of the sample

The three scenarios represent different forms of the consulting situation. The "Human Consulting" scenario (n ≈ 24) describes a classic face-to-face consulting situation. In the "AI Consulting" scenario (n ≈ 23), the recommendation is based entirely on an AI system without personal interaction. The "hybrid consulting" scenario (n ≈ 37) combines human consulting and AI support.

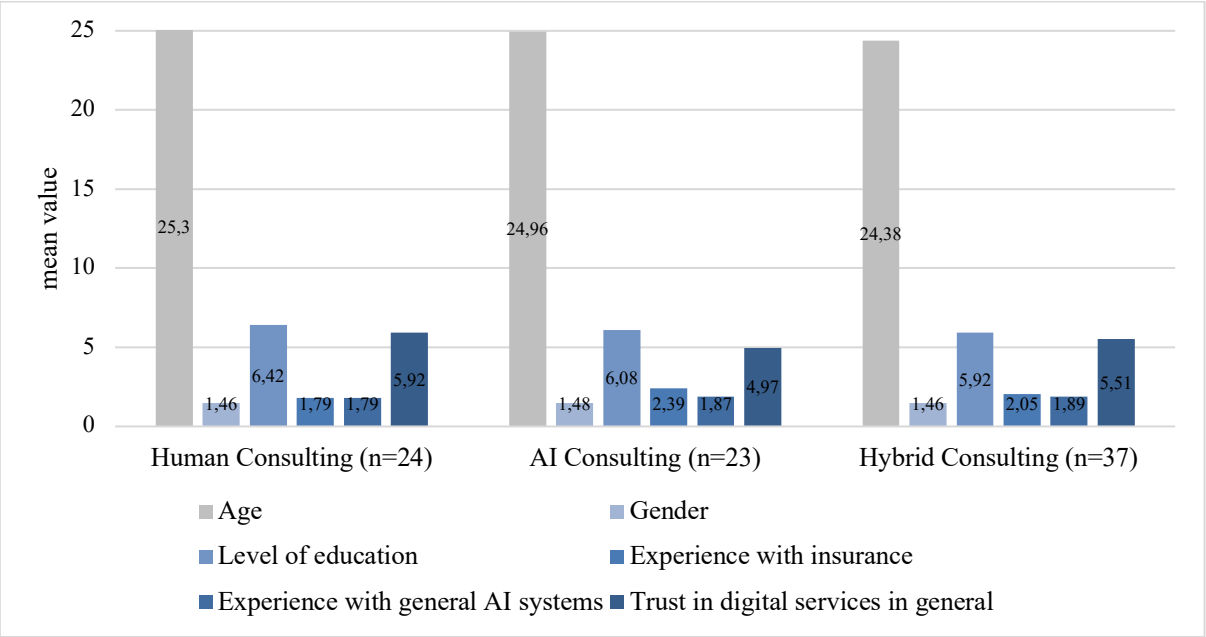

Figure 2: Descriptive statistics for the three subsamples "Human Consulting," "AI Consulting," and "Hybrid Consulting."[4]

[4]Own representation based on the results of this study.

Figure 2 presents the descriptive statistics (mean values) for three subsamples: "Human Consulting," "AI Consulting," and "Hybrid Consulting." The mean ages in all groups are quite similar, with the following values: Human Consulting (M = 25.30), AI Consulting (M = 24.96), and Hybrid Consulting (M = 24.38). Regarding the gender variable, coded in SPSS as 1 = female, 2 = male, and 3 = diverse, the mean values across all three groups are close to 1.5. Specifically, the mean values are: Human Consulting (M = 1.46), AI Consulting (M = 1.48), and Hybrid Consulting (M = 1.46). This indicates a predominantly female sample. For the level of education, which is coded ordinally from 1 = no school leaving certificate to 8 = other, the mean values are as follows: Human Consulting (M = 6.42), AI Consulting (M = 6.08), and Hybrid Consulting (M = 5.92). All groups fall within the tertiary education sector. In detail, a mean value of 6.42 corresponds to an average education level within the bachelor's degree range (category 6), with a slight inclination toward a master's degree (category 7). The mean value of 6.08 clearly indicates a bachelor's degree level, while 5.92 lies on the threshold between vocational training (category 5) and a bachelor's degree (category 6). Experience with insurance is coded such that lower values indicate more contracts concluded (1 = 3+ contracts, 2 = 1-2 contracts, 3 = “don't know,” 4 = no information provided, 5 = no contracts).

Accordingly, the human consulting group has the highest average contract experience, with a mean (M) of 1.79. The hybrid group follows with a mean of 2.05, while the AI consulting group has the least contract experience, with a mean of 2.39. Experience with general AI systems is coded as 1 = occasional use (weekly), 2 = regular use (daily), and 3 = no experience. Mean values for experience with AI systems range between 1.79 and 1.89. Specifically, the mean for the human group is 1.79, the AI group is 1.87, and the hybrid group is 1.89, indicating that respondents in all groups use AI on average between weekly and daily. Trust in digital services was measured using a seven-point Likert scale. The mean values reflect a relatively high to upper-middle level of trust among the groups: human consulting shows the highest average trust with a mean of 5.92, followed by hybrid consulting at 5.51, while AI consulting has the lowest mean value of 4.97. The following sections will systematically compare these three scenarios. Transparency and traceability of the recommendations will be discussed in Equation 2.

Transparency and traceability of the recommendation (Equation 2)

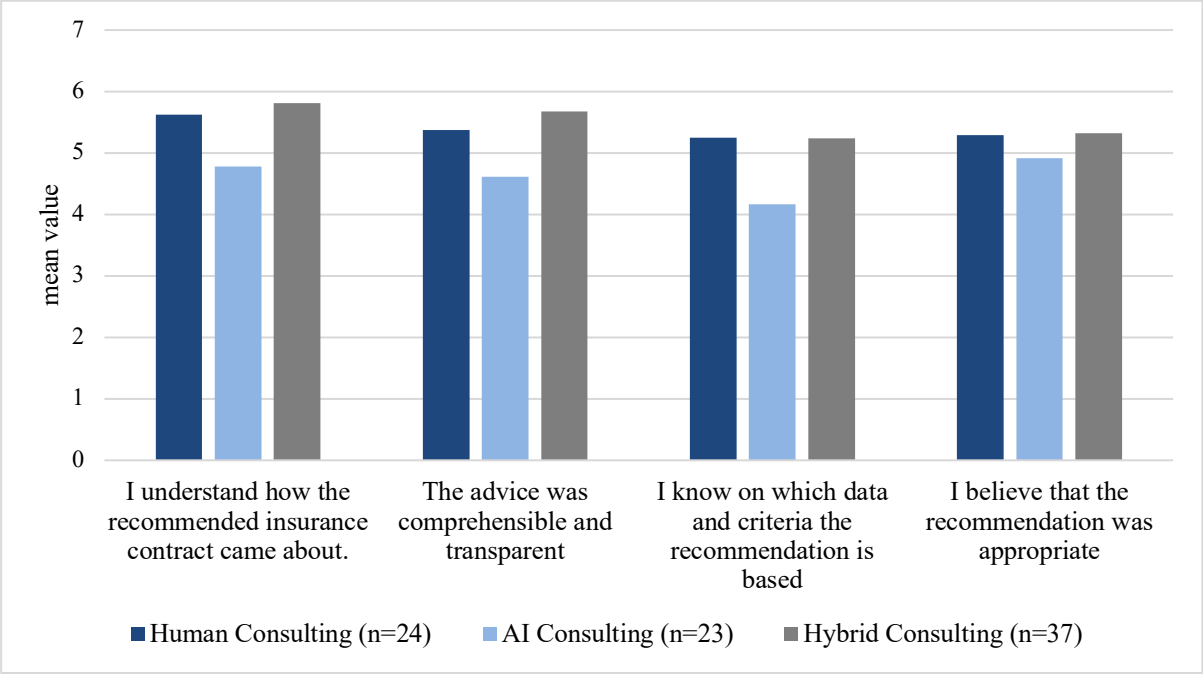

Figure 3: Descriptive statistics of Transparency and traceability of the recommendation[5]

For the item "I understand how the recommended insurance contract came about," the results were as follows: In the human consultation scenario (n = 24), the mean score was M = 5.62 (SD = 1.527). In the AI advice scenario (n = 23), the mean value was M = 4.78 (SD = 1.999). In the hybrid advice scenario (n = 37), the mean score was M = 5.81 (SD = 1.525). The overall comprehensibility of the advice, measured by the statement "The advice was comprehensible and transparent," was rated at M = 5.37 (SD = 1.377) in the human advice scenario (n = 24). For the AI advice scenario (n = 23), the mean score was M = 4.61 (SD = 1.725), while in the hybrid advice scenario (n = 37), the mean was M = 5.68 (SD = 1.270). Regarding knowledge of the basis for decision-making, indicated by "I know on which data and criteria the recommendation is based," the results were as follows: M = 5.25 (SD = 1.726) for human consulting (n = 24), M = 4.17 (SD = 2.015) for AI consulting (n = 23), and M = 5.24 (SD = 1.553) for hybrid advice (n = 37). Finally, the perceived appropriateness of the recommendation, expressed as "I believe that the recommendation was appropriate," yielded the following scores: M = 5.29 (SD = 1.233) for human consulting (n = 24), M = 4.91 (SD = 1.311) for AI consulting (n = 23) and M = 5.32 (SD = 1.334) for hybrid consulting (n = 37).

[5] Own representation based on the results of this study.

Assignment of responsibility (Equation 3)

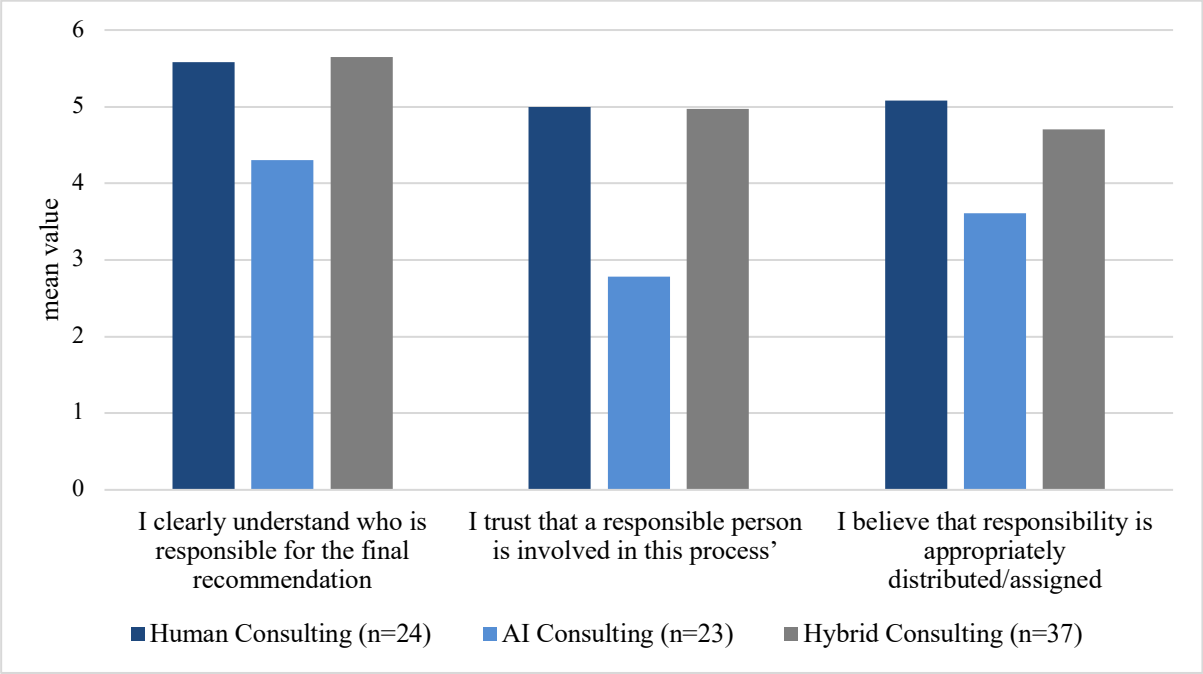

Figure 4: Descriptive statistics of Assignment of responsibility[6]

The clarity of responsibility was assessed with the statement, "I clearly understand who is responsible for the final recommendation." In the human consulting scenario (n = 24), the mean was M = 5.58 with a standard deviation (SD) of 1.742. For AI advice (n = 23), the mean was M = 4.30 (SD = 2.032). In the hybrid advice scenario (n = 37), the mean score was M = 5.65 (SD = 1.567). Regarding the statement, "I trust that a responsible person is involved in this process," human consulting yielded a mean of M = 5.00 (SD = 1.794) with 24 participants. In AI consulting (n = 23), the mean was significantly lower at M = 2.78 (SD = 1.536). For hybrid consulting (n = 37), the mean score was M = 4.97 (SD = 1.641). The assessment of responsibility distribution was evaluated with the statement, "I believe that responsibility is appropriately distributed/assigned." In human consulting (n = 24), the mean was M = 5.08 (SD = 1.501). In AI consulting (n = 23), the mean was M = 3.61 (SD = 1.500), and in hybrid consulting (n = 37), the mean was M = 4.70 (SD = 1.450).

[6] Own representation based on the results of this study.

Trust in the advisor (Equation 4)

The evaluation of professional competence indicated that human consulting had a mean score of M = 5.68 (SD = 1.171) based on 22 responses. In contrast, the AI consulting scenario had only two valid responses (n = 2), resulting in a mean of M = 5.00 (SD = 1.414). For hybrid consulting, the mean score was M = 5.25 (SD = 1.414) based on 32 responses. Regarding the statement "I believe that he/she is acting in my best interest," the mean score in human consulting was M = 4.91 (SD = 1.269) from 22 participants. In the AI consulting scenario, the mean score was M = 5.00 (SD = 2.828) based on the two valid responses. In hybrid consulting, the mean was M = 4.94 (SD = 1.014) from 32 responses. For perceived personal integrity, as reflected in the statement "I consider him/her to be honest and reliable," the mean score for human consulting was M = 5.18 (SD = 1.140) from 22 participants. For AI consulting, the mean was M = 5.00 (SD = 2.828) with n = 2. In hybrid consulting, the mean was M = 4.84 (SD = 1.194) from 32 participants. Note: The key figures for AI consulting in this section are based on only two responses, because these items were only shown in the human and hybrid scenarios; the AI-only values are based on two isolated responses and are not considered meaningful.

Trust in AI (Equation 5)

Trust in the AI system was assessed using several statements. The statement "The system provides objective and accurate recommendations" resulted in a mean score of M = 3.50 (SD = 0.707) in human consulting (n = 2). In AI consulting (n = 22), the mean score was M = 4.91 (SD = 1.540). For hybrid consulting (n = 33), the mean score was M = 5.24 (SD = 1.119). For the statement "I consider AI to be reliable," the mean score in human consulting (n = 2) was M = 5.00 (SD = 1.414). In AI consulting (n = 22), the mean score was M = 4.50 (SD = 1.472), while in hybrid consulting (n = 33), the mean reported was M = 4.97 (SD = 1.468). The statement "I trust that AI makes fair decisions" yielded a mean score of M = 3.50 (SD = 0.707) in human consulting (n = 2). In AI consulting (n = 22), the mean score was M = 4.23 (SD = 1.541), and for hybrid consulting (n = 33), the mean value was M = 4.48 (SD = 1.503). Overall, trust in the AI system was moderate across all three scenarios, with slightly higher mean values in the AI and hybrid consulting conditions. A graphical overview of trust in the AI system and in the insurance company across the different scenarios is provided in Figure 5.

Trust in the insurance company as an organization (Equation 6)

In terms of general trust in the company ("I trust the insurance company as a company"), the average score for human consulting (n = 24) was M = 4.46 (SD = 1.474). For AI consulting (n = 23), the average was M = 4.43 (SD = 1.441), while in hybrid consulting (n = 37), the mean score was M = 4.70 (SD = 1.222). Regarding perceived ethical and transparent working methods ("The company appears ethical, moral, and transparent to me"), the average for human consulting (n = 24) was M = 4.37 (SD = 1.245). In AI consulting (n = 23), the mean score was M = 4.13 (SD = 0.869), whereas in hybrid consulting (n = 37), the average increased to M = 4.81 (SD = 0.908). For the assessment of the company's use of AI ("I believe that the company uses AI responsibly"), the mean score in human consulting was M = 4.00 (SD = 1.414) based on n = 2 participants. For AI consulting (n = 22), the average score was M = 4.45 (SD = 1.371), and in hybrid consulting (n = 33), the mean rose to M = 5.03 (SD = 1.159). When evaluating the qualification for recommendation activities ("I believe that the company trains its employees well to make responsible and informed recommendations"), the average for human consulting (n = 22) was M = 4.82 (SD = 1.181). In AI consulting (n = 2), the mean was notably higher at M = 5.50 (SD = 2.121), while in hybrid consulting (n = 32), it was M = 5.03 (SD = 1.062).

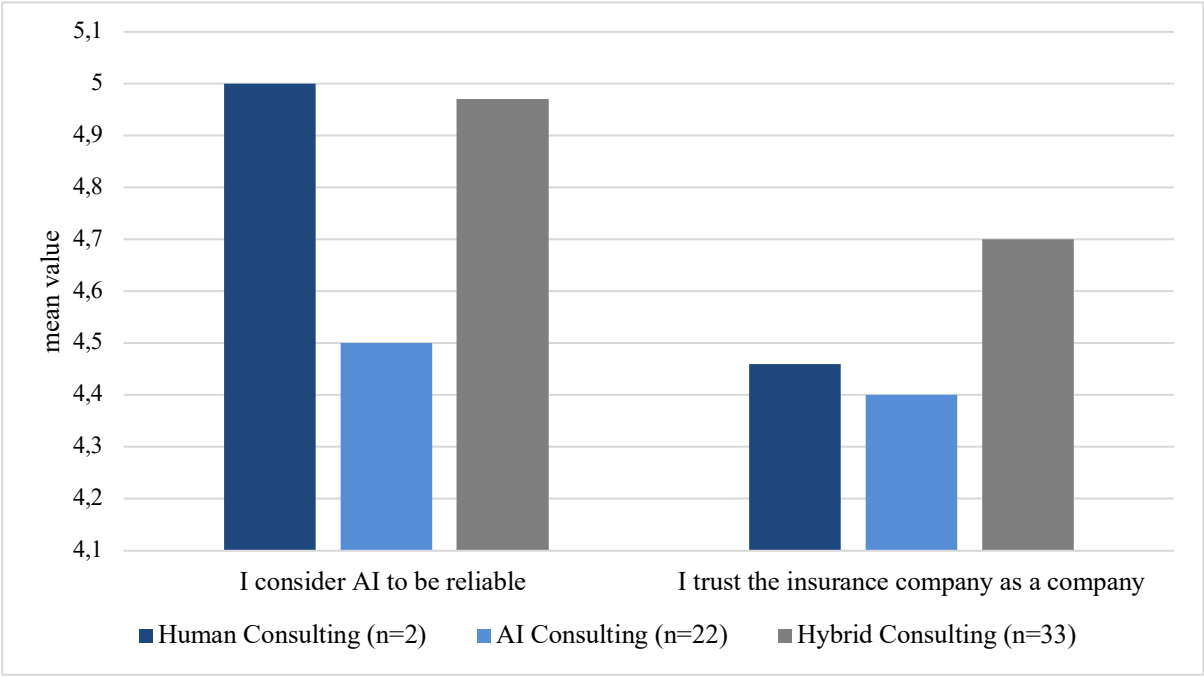

Figure 5: Trust in the AI system and in the insurance company according to consultation scenario[7]

[7] Own representation based on the results of this study.

Figure 5 illustrates the trust in the AI system and the insurance company according to the different consultation scenarios. The trust in the AI system is slightly higher in the hybrid scenario compared to the pure AI scenario and is roughly comparable to the human advisory scenario, although the human scenario value is based on just n = 2 participants. Trust in the insurance company itself is moderate across all three scenarios, with a slight preference for the hybrid scenario.

Perceived quality of advice (Equation 7)

The assessment of whether the advice contributed to the decision-making process ("This form of advice helped me make the right decision") showed a mean score of 5.12 (SD = 1.262) for human advice (n = 24). In AI consulting (n = 23), the mean score was 4.48 (SD = 1.410). In hybrid consulting (n = 37), the mean score was 5.05 (SD = 1.311). Regarding the perceived efficiency of the decision-making process ("This type of consulting makes the decision-making process easier and more efficient for me"), the mean score in human consulting was 4.96 (SD = 1.233) with 24 respondents. In AI consulting, the result was 5.30 (SD = 1.295) from 23 respondents. In hybrid consulting, the mean score was also 5.30 (SD = 1.488) from 37 respondents. For the intention to use the consulting again in the future ("I would use this type of consulting again"), the mean score for human consulting was 4.96 (SD = 1.601) with 24 respondents. In AI consulting, the mean score was the same, 4.96 (SD = 1.609) from 23 respondents. In hybrid consulting, the mean score increased to 5.35 (SD = 1.549) from 37 respondents. Finally, for the willingness to recommend the consulting to friends ("I would recommend this type of consulting to my friends"), the mean score for human consulting was 4.75 (SD = 1.422) with 24 respondents. In AI consulting, the result was slightly lower at 4.74 (SD = 1.389) from 23 respondents. In hybrid consulting, the mean score improved to 5.05 (SD = 1.413) with 37 respondents.

Transparent communication and traceability (Equation 8)

Perceived data security, measured by the statement "I have the impression that the provider handles my personal data responsibly (data protection)," had a mean score of M = 5.42 (SD = 1.840) in human consulting (n = 24). In AI consulting (n = 23), the mean score was M = 4.57 (SD = 1.701). For hybrid consulting (n = 37), the mean score was M = 5.46 (SD = 1.282). Regarding the openness of information sharing, assessed by the statement "I felt that all important information was communicated to me openly," the mean was M = 4.71 (SD = 1.517) in human consulting (n = 24). In AI consulting (n = 23), the result was M = 4.13 (SD = 1.604). In hybrid consulting (n = 37), the mean score was M = 5.32 (SD = 1.132). The comprehensibility of the decision-making process, measured by "I could understand how the recommendation was arrived at," yielded a mean of M = 5.29 (SD = 1.459) in human consulting (n = 24). In AI consulting (n = 23), the result was M = 3.83 (SD = 1.497), while in hybrid consulting (n = 37), the mean score was M = 5.57 (SD = 1.214). Only two respondents answered the question regarding the handling of new technology, expressed as "The provider gives the impression of dealing with new technologies (AI) in a responsible and compliant manner." In human consulting (n = 2), the mean score was M = 2.00 (SD = 1.414). In AI consulting (n = 22), the result was M = 4.82 (SD = 1.368), and in hybrid consulting (n = 33), the mean score was M = 5.36 (SD = 1.025).

Loyalty to the company (Equation 9)

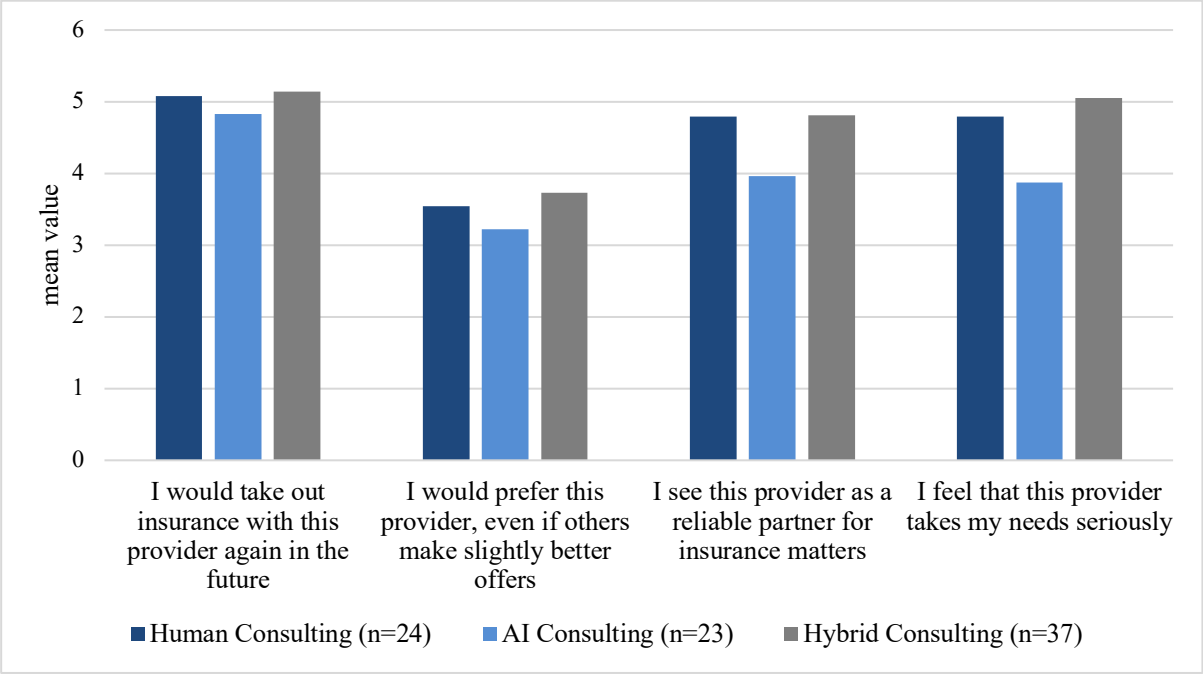

Figure 6: Descriptive statistics of Loyalty to the company[8]

The willingness to take out a policy, assessed by the statement "I would take out insurance with this provider again in the future," showed a mean score (M) of 5.08 with a standard deviation (SD) of 1.501 for human consulting (n = 24). In the AI advice condition (n = 23), the mean score was 4.83 (SD = 1.337). For hybrid advice (n = 37), the mean score increased to 5.14 (SD = 1.337). Provider preference was evaluated through the statement "I would prefer this provider, even if others make slightly better offers." The mean score for human consulting was 3.54 (SD = 1.956), while in AI consulting, it was lower at 3.22 (SD = 1.126). In the hybrid consulting group, the mean score was 3.73 (SD = 1.694). When assessing the provider as a reliable partner, indicated by the statement "I see this provider as a reliable partner for insurance matters," the mean score for human consulting was 4.79 (SD = 1.532). In AI consulting, the score was 3.96 (SD = 1.261), and in hybrid consulting, it was 4.81 (SD = 1.151). Lastly, the perceived need orientation, measured by "I feel that this provider takes my needs seriously," yielded a mean score of 4.79 (SD = 1.532) in human consulting. In AI consulting, the mean score was 3.87 (SD = 1.359), while the hybrid consulting group had a mean score of 5.05 (SD = 1.268).

[8] Own representation based on the results of this study.

Acceptance of AI-supported decisions (Equation 10)

The item "I feel uncomfortable when AI decides on insurance matters" received a score of n = 2 with a mean of M = 6.50 (SD = 0.707) in human consulting. In AI-based consulting (n = 22), the mean score was M = 3.82 (SD = 1.680). In hybrid consulting (n = 33), the mean score was M = 3.85 (SD = 1.873). For the statement "I prefer human assessments to AI recommendations," the mean score in human consulting (n = 24) was M = 4.67 (SD = 1.834). In AI consulting (n = 23), the mean score was M = 4.43 (SD = 2.107). In hybrid consulting (n = 37), the mean score was M = 4.73 (SD = 1.805). Regarding long-term trust in AI ("If AI delivers good results, I trust it in the long term"), the mean score in human consulting (n = 24) was M = 5.08 (SD = 1.412). In AI consulting (n = 23), the result was M = 5.17 (SD = 1.114). In hybrid consulting (n = 37), the mean score was M = 5.14 (SD = 1.456). For the need for control ("I would feel more comfortable if AI decisions were reviewed by a person"), the mean score was M = 5.29 (SD = 1.756) in human consulting (n = 24). In AI consulting (n = 23), the result was M = 5.43 (SD = 1.854). In hybrid consulting (n = 37), the mean score was M = 5.46 (SD = 1.726).

Attitude toward AI (Equation 11)

The general interest in AI, measured by the statement "I find it exciting when AI is used in everyday life," yielded the following results: In human consulting (n = 24), the mean score was M = 6.25 (SD = 1.225). In AI consulting (n = 23), the mean was M = 6.04 (SD = 1.224). In hybrid consulting (n = 37), the mean score was M = 5.68 (SD = 1.600). Regarding personal well-being with AI support, assessed by the statement "I feel comfortable when AI supports decisions that affect me," the results were as follows: In human consulting (n = 24), the mean was M = 5.33 (SD = 1.579). In AI consulting (n = 23), the mean score was M = 5.22 (SD = 1.506). In hybrid consulting (n = 37), the mean was M = 4.97 (SD = 1.384). Lastly, for opportunity orientation, defined by the statement "I see AI as an opportunity rather than a risk," the results were: In human consulting (n = 24), the mean score was M = 5.63 (SD = 1.583). In AI consulting (n = 23), the mean was M = 5.43 (SD = 1.273). In hybrid consulting (n = 37), the mean score was M = 5.16 (SD = 1.692).

Inferential statistical analysis

The hypotheses are tested using inferential statistics, applying bivariate correlations, t-tests and ANOVA to examine whether the observed differences between the consulting scenarios are statistically significant.

Testing Hypothesis 1 (Equation 12)

> *Hybrid human-AI consulting generates greater trust, a more positive perception of fairness and transparency, and clearer attribution of responsibility than pure AI consulting.*

In terms of trust in the advice (measured by a trust index consisting of three items), descriptive analysis indicated a higher mean value in the hybrid condition (M = 4.93; SD = 0.95; n = 28) compared to pure AI advice (M = 4.55; SD = 1.31; n = 22). However, the t-test for independent samples revealed no significant difference between the two groups, t (48) = -1.20, p = .237 (two-tailed). An ANOVA was also performed with scenario as a factor, but no significant overall effect was found, F (2, 69) = 2.30, p = .108, with an effect size of $\eta^2 = .06$. Descriptively, the expected ranking emerged: the highest level of trust was attributed to purely human advice (M = 5.26; SD = 1.05; n = 22), followed by hybrid advice (M = 4.93; SD = 0.95; n = 28), while pure AI advice was rated lowest (M = 4.55; SD = 1.31; n = 22).

However, the differences between the scenarios do not reach statistical significance in the overall comparison. More pronounced effects were observed regarding perceived transparency in the consulting process. Pure AI consulting received the lowest rating (M = 4.62; SD = 1.41; n = 23), while hybrid consulting received a significantly higher rating (M = 5.51; SD = 1.26; n = 37). The corresponding t-test revealed a significant difference favoring hybrid consulting, t (58) = -2.55, p = .013 (two-tailed). An ANOVA with four groups (including a small group labeled "no clear assignment") indicated a marginally significant overall effect of the scenario, F (3, 85) = 2.63, p = .055, with an effect size of $\eta^2 = .09$. The mean values supported this, showing the lowest perception of transparency in the AI-only condition (M = 4.62) and higher values in the human consulting (M = 5.39) and hybrid consulting (M = 5.51) conditions. The differences were most pronounced in the perceived assignment of responsibility (accountability). Participants in the AI-only condition reported significantly lower values (M = 3.57; SD = 1.39; n = 23) compared to participants in the hybrid condition (M = 5.11; SD = 1.32; n = 37). The mean difference of -1.54 points on a 7-point scale was highly significant, t (58) = -4.31, $p < .001$ (two-tailed). The ANOVA revealed a highly significant effect of the scenario

on perceived responsibility, $F(3, 85) = 7.19$, $p < .001$, with an effect size of $\eta^2 = .20$.The mean values indicated that AI-only was rated the lowest ($M = 3.57$), while both human consulting ($M = 5.22$) and hybrid consulting ($M = 5.11$) were rated significantly higher, though at similar levels. Overall, Hypothesis 1 is partially supported. Hybrid consulting yields significantly higher perceived transparency and clearer responsibility attribution than pure AI consulting. In contrast, the expected trust advantage for hybrid consulting is not statistically significant in this sample and is only descriptive.

Testing Hypotheses 2 (Equation 13)

> *Greater trust and more positive perceptions of transparency/fairness and accountability lead to greater customer loyalty toward the insurance provider.*

The bivariate correlations show that all three predictors are significantly positively correlated with customer loyalty: trust ($r = .605$, $p < .001$), transparency/traceability ($r = .594$, $p < .001$), and accountability ($r = .578$, $p < .001$). Consequently, customer loyalty increases significantly with trust, which is the strongest single predictor. The mean values also show that loyalty is in the upper mid-range (Loyalty: $M = 4.47$; $SD = 1.22$; $N = 72$). Trust ($M = 4.91$; $SD = 1.12$), transparency ($M = 5.27$; $SD = 1.32$), and accountability ($M = 4.79$; $SD = 1.60$) were all rated relatively high. In a multiple linear regression analysis, where loyalty served as the dependent variable and trust, transparency, and accountability were used as simultaneous predictors, a highly significant overall model was obtained ($F (3, 68) = 23.06$; $p < .001$), with an explained variance of $R^2 = .504$ (corrected $R^2 = .482$). Trust emerged as a strong and significant predictor ($B = 0.397$; beta = .367; $p < .001$), as did the assignment of accountability ($B = 0.216$; beta = .284; $p = .015$). However, the effect of transparency remained insignificant in the overall model ($B = 0.183$; beta = .199; $p = .115$).

Overall, higher trust in advice and a clear allocation of accountability are closely associated with significantly greater loyalty to the insurance provider, while transparency appears to contribute more indirectly through these two factors[9].

[9] Refers to trust and accountability.

Testing Hypotheses 3 (Equation 14)

> *Within Gen Z: The more positive the personal attitude toward AI, the higher the acceptance of AI decisions.*

The correlation between general attitudes toward AI and the acceptance of AI decisions was nearly nonexistent ($r = -.01$, $p = .49$). Additionally, the regression model was insignificant, with $F(1, 53) = 0.001$, $p = .972$, and it explained almost no variance ($R^2 = .000$). The standardized regression coefficient ($\beta = -.005$, $p = .972$) indicates that general attitudes toward AI do not significantly contribute to explaining the acceptance of specific AI-supported decisions in consulting. Consequently, Hypothesis H3 is not confirmed; among the Gen Z sample surveyed, a more positive general attitude toward AI does not result in greater acceptance of specific AI-supported decisions in the insurance domain.

5 Discussion

Overall, the results suggest that hybrid consulting formats for Gen Z in the insurance context strike the "optimal balance of efficiency and reassurance," (Dennstedt & Targan, 2025; Gaedeke, 2024; Gerhardus, 2023a). Specifically, the mean values and variance analyses show that AI-only consulting is rated lowest in terms of transparency/comprehensibility (M = 4.62), while hybrid (M = 5.51) and human (M = 5.39) consulting are rated significantly higher, indicating differences in perceived explainability. The attribution of responsibility is even more clearly differentiated. In the AI-only condition, it is significantly lower (M = 3.57), while hybrid (M = 5.11) and human (M = 5.22) signal "clear responsibility". In terms of trust, there is a slightly order in descriptive values (human > hybrid > AI-only), but without significant differences, which can be interpreted in terms of context-dependent, more stable trust building. For loyalty, multiple regression shows that trust (β = .367) and attribution of responsibility (β = .284) are significant predictors, while transparency is not significant in the overall model. In addition, it appears that a generally positive attitude toward AI does not automatically increase acceptance of specific AI decisions in this sensitive area, which relativizes common, simplified assumptions about acceptance. The results fit squarely into what research now says, insurance consulting is moving away from face-to-face ties built over years and toward setups that use many channels, hard data plus algorithms.

Perception of transparency

The results show that transparency and comprehensibility are perceived differently in the three scenarios. As mentioned above the transparency value is the lowest in the AI-only scenario (M = 4.62; SD = 1.41; n = 23). Hybrid (M = 5.51; SD = 1.26; n = 37) and human (M = 5.39; SD = 1.52; n = 24) achieve significantly higher values. The direct comparison of hybrid with AI-only is significant ($t(58) = -2.553$; $p = .013$). The effect is relevant in terms of content (Cohen's $d \approx 0.68$). This corresponds to a medium to large difference (Cohen, 2009). The overall ANOVA narrowly misses significance ($F(3,85) = 2.634$; $p = .055$). Nevertheless, the effect size ($\eta^2 = .09$) shows a noticeable format effect because η^2 indicates the proportion of variance explained by the consulting format (Backhaus et al., 2021; Cohen, 2009). This clearly shows where pure AI reaches its limits when it comes to understanding the decision-making process.

The statement "I could understand how the recommendation was made" achieves an average of 3.83 (SD = 1.50) for AI-only. Hybrid and human are significantly higher at 5.57 (SD = 1.21)

and 5.29 (SD = 1.46) respectively. According to Gaedeke (2024), a significant proportion of Gen Z feels "overwhelmed" in the insurance market and seeks clear, structured decision-making criteria. A similar picture emerges when it comes to understanding the basis for the decision. The statement “I know what data or criteria the recommendation is based on” scores 4.17 (SD = 2.02) for AI-only. For hybrid and human, the scores are around 5.24 and 5.25, respectively. Hersch et al. (2022) point out that Gen Z customers consider algorithmically generated recommendations to be non-transparent unless explicit explanations of the decision-making logic are provided. As is common with online advice systems, the AI advice in this study was not explanation-based, which is consistent with the findings of Hersch et al. (2022) and Kern & Loh (2024) on the “black box effect” of algorithmic systems. The higher transparency rating of the hybrid scenario can be theoretically understood through the concept of "human mediation", as described by Heyder et al. (2023).

Human advisors provide social anchors of explanation and trust that purely algorithmic systems cannot offer. Pure AI is therefore not rated worse across the board but is perceived as less comprehensible. These findings are consistent with what studies on Gen Z and insurance companies report. Dennstedt and Targan (2025) show that Gen Z often finds insurance confusing and therefore needs clear, structured information. Gaedeke (2024) describes how Gen Z is looking for guidance in the insurance market and finds simple criteria helpful. Gerhardus (2023a) emphasizes that Gen Z rates advice positively when complexity is translated into understandable language. This translation is missing in the AI-only scenario, which is why process traceability is particularly low there. The literature on explainable AI (XAI) systems confirms this interpretation. Shin (2021) shows that explanations increase user perception of transparency and acceptance because they allow decisions to be better scrutinized. Zhou et al. (2021) argue that judgments about fairness or trust in algorithmic decisions depend heavily on whether the process is perceived as comprehensible. This fits with the study, the central weakness of AI-only lies in its lack of traceability.

The results also show that transparency is defined more broadly here. It also includes impressions of data responsibility and openness in communication. For the item “handles my personal data responsibly,” AI-only scores M = 4.57 (SD = 1.70), hybrid scores M = 5.46 (SD = 1.28), and human scores M = 5.42 (SD = 1.84). For the item “all important information was communicated openly,” AI-only scored M = 4.13 (SD = 1.60), hybrid scored M = 5.32 (SD = 1.13), and human scored M = 4.71 (SD = 1.52). This means that AI-only not only lacks an understanding of the process, but also a sense of openness and responsible handling of data.

These findings are consistent with studies that examine trust in digital brands. Ali et al. (2025) show that trust arises when providers act openly and behave ethically, especially when customers cannot understand the process themselves. This is particularly important in the insurance business, where sensitive personal data and high financial risks are involved (Ali et al., 2025). The supervisory authority confirms this view, EIOPA (2024) explains that digitalization in insurance raises questions about corporate governance and consumer protection. Transparency and responsible management are central to this. Kern and Loh (2024) emphasize that artificial intelligence is only considered trustworthy if explainability and verifiability are not only technically available but also perceptible to the user. The lower scores in the AI-only approach indicate that pure automation without visible embedding sends less credible transparency signals.

Attribution of responsibility

The attribution of responsibility shows the greatest difference between the scenarios. The accountability value is lowest in the AI-only scenario ($M = 3.57$; $SD = 1.39$). The values for hybrid ($M = 5.11$; $SD = 1.32$) and human ($M = 5.22$; $SD = 1.55$) are significantly higher. The difference between hybrid and AI-only is highly significant ($t(58) = -4.314$; $p < .001$). The effect size is very large (Cohen's $d \approx 1.15$), indicating a strong difference (Cohen, 2009). The ANOVA also shows clear significance ($F(3,85) = 7.191$; $p < .001$) with a large effect size ($\eta^2 = .20$). This means that a considerable part of the differences in responsibility judgments can be attributed to the consulting format (Backhaus et al., 2021; Cohen, 2009). The pattern stands out most clearly when each statement is examined on its own. For the statement “I trust that a responsible person is involved in this process,” the average response is 2.78 ($SD = 1.54$) when only AI is used. When a hybrid approach is used the average rises to 4.97 ($SD = 1.64$) and when only humans are involved it is 5.00 ($SD = 1.79$). Those numbers show that a large share of participants who saw the AI-only version do not believe a clearly accountable person is part of the process. There is also less understanding of who is responsible.

Studies by Miller (2025) and Elizabeth (2025) indicate that Gen Z customers regard insurance decisions as "high-stakes decisions," leading them to demand a human authority for oversight. This assessment aligns with the findings of this study, which demonstrate that perceptions of human responsibility are significantly higher in hybrid scenarios. These results not only corroborate existing literature but also provide empirical evidence of the extent to which Gen Z's perception of responsibility influences their evaluation of advisory concepts.

Notably, the responsibility factor remains a significant predictor of loyalty in the regression analysis, a relationship that has not been clearly documented in insurance research to date and therefore represents an interesting starting point for further studies. For the item “I clearly understand who is responsible,” the mean score is 4.30 in the AI-only scenario, 5.65 in the hybrid scenario, and 5.58 in the human scenario. In the AI-only scenario, this creates a gap when it comes to who is responsible. The literature provides an accurate explanation for this. Do Khac and Leyer (2025) state that acceptance of decisions made by humans and AI only arises when responsibilities are clearly defined and the user knows who is responsible in the event of a dispute. Heyder et al. (2023) call for human-AI systems to be designed in such a way that responsibility does not disappear into a “disappears”. Rieger et al. (2025) show that even a reliable decision-making system creates problems as soon as the psychological assignment of responsibility becomes unclear. These statements fit exactly with the present findings, AI-only seems less responsible, while hybrid systems visibly restore responsibility. The fact that responsibility plays such an important role in insurance can be explained by the context. Decisions in this industry have an impact on financial risks and consequences that become apparent years later. That is why supervision, control, and clear responsibility are key (EIOPA, 2024).

Hacker and Eber (2025) show that AI in insurance and credit requires particularly careful responsibility structures because the decisions are far-reaching. Capraro (2024) also points out that unclear governance increases social risks. The literature thus explains why responsibility decreases significantly in a pure AI scenario. An important secondary finding is that AI-only is considered efficient but is not perceived as particularly reliable for decision-making. For the item “makes the decision-making process easier and more efficient,” AI-only achieved M = 5.30, hybrid also achieved M = 5.30, and human achieved M = 4.96. For “helped me make the right decision,” AI-only scored M = 4.48, below human (M = 5.12) and hybrid (M = 5.05). Although the test subjects recognize efficiency advantages, they are more skeptical that the decision was correct. This distinction is well articulated in the existing literature. Candreia et al. (2024) illustrate that insurers place a significant emphasis on efficiency and automation in their digital journeys. Bughin et al. (2017) contend that digital transformation is frequently driven by speed and a data-centric approach. Concurrently, literature targeting Gen Z within the insurance sector reveals that while digital solutions are anticipated, comprehensibility and security are paramount when confronting complex decision-making scenarios (Dennstedt & Targan, 2025; Gaedeke, 2024; Gerhardus, 2023a). Witt and Schissler (n.d.) underscore that the

customer experience for Gen Z in insurance is heavily contingent upon the clarity and security of the processes involved. This aligns with the finding that efficiency alone is inadequate in the absence of transparency and accountability.

Trust as a stable, context-sensitive factor

The Trust Index indicates a ranking among the different formats, human, hybrid, and AI-only, with the expected order being human > hybrid > AI-only. However, the statistical analysis reveals that these differences are not significant ($t(48) = -1.196$, $p = .237$; ANOVA $F(2,69) = 2.30$, $p = .108$; $\eta^2 = .06$). Hence, within this sample, it cannot be concluded with statistical certainty that a distinct difference in trust exists among the formats. The existing literature provides a plausible rationale for these findings. Mayer et al. (2007) characterize trust as a relatively stable construct that is influenced by factors such as competence, integrity, and benevolence, which typically develop over time. Additionally, Morgan and Hunt (1994) frame trust as the fundamental mechanism underlying long-term relationships. Gen Z customers exhibit a comparatively high level of baseline trust in digital technologies (Merriman et al., 2023) but they make clear distinctions between lifestyle applications and contexts that involve risk or safety (Dewalska-Opitek et al., 2024).

Moreover, technology acceptance models illustrate that attitudes and intentions regarding technology usage are highly context-dependent and are often shaped and stabilized by experience (Davis, 1987; Venkatesh et al., 2003). Trust does not change in the short based on a single usage experience rather, it evolves through repeated interactions that foster a sense of situational security. This sensitivity to context is particularly pronounced in the insurance sector, which involves high financial stakes, compared to many other areas of consumption (Miller, 2025). The slightly higher trust ratings for hybrid advice can therefore be cautiously interpreted in the light of theoretical literature: the combination of algorithmic efficiency and human integrity creates what Gerhardus et al. (2024) describes as a “trust-promoting human-machine symbiosis”. The integration of a human counterpart who not only explains but is also perceived as a moral and intentional authority increases trust stability. Consequently, in scenarios governed by specific contexts, aspects such as transparency or accountability may be more impactful than trust itself, given that trust frequently necessitates a foundation of repeated interactions (2025).

Loyalty: The importance of trust and responsibility

The regression analysis shows which factors independently explain loyalty in this study. The regression model is highly significant ($F(3,68) = 23.057$, $p < .001$) and explains about half of the differences in loyalty ($R^2 = .504$; adj. $R^2 = .482$). This means that loyalty in this sample is not only "coincidentally" related to the scenarios but can be explained to a large extent by the variables examined (Backhaus et al., 2021; Stockemer & Bordeleau, 2023). In the model, trust is the strongest influencing factor, trust is significant ($\beta = .367$; $t = 3.522$; $p = .001$). Simply put, the higher the trust, the higher the loyalty. This fits well with the literature. Morgan and Hunt (1994) describe trust as the central basis for long-term customer relationships. This is particularly plausible for insurance companies because insurance products are difficult to evaluate directly, which means that customers tend to rely more on signals of trust (Eickenberg, 2022).

Minta (2025) also emphasizes that loyalty in the insurance industry depends heavily on trust but also on relationship quality. In addition to trust, accountability also proves to be a significant predictor ($\beta = .284$; $t = 2.484$; $p = .015$). This means that loyalty increases when respondents feel that there is a clear allocation of responsibility. This finding is significant because it shows that loyalty does not depend solely on "trust in general," but also on whether a responsible person or clear responsibility is identifiable. This ties in seamlessly with Do Khac and Leyer (2025), who argue that acceptance of human-AI collaboration requires clear accountability structures so that users know who is responsible for decisions in case of doubt. Transparency is not significant in the regression model ($\beta = .199$; $t = 1.598$; $p = .115$). However, the bivariate correlation shows that transparency is strongly related to loyalty ($r = .594$; $p < .001$). This is not a contradiction. It means that transparency is important but does not make an additional contribution to the model when trust and responsibility are already considered.

Methodologically, this is because transparency and trust are interrelated and their effects partially overlap in the model (Backhaus et al., 2021). In terms of content, this is consistent with the literature, Shin (2021) shows that explainability is effective primarily because it strengthens trust but also acceptance. Zhou et al. (2021) argue that perceptions of fairness influence trust. It follows that transparency indirectly promotes loyalty by supporting trust (and fairness). Trust then increases loyalty. In summary, this section shows that loyalty in this study is primarily explained by trust and clear attribution of responsibility. Transparency also plays a role, but rather indirectly, because it primarily influences trust and perceptions of fairness.

Lack of effect of AI attitude on acceptance

The results show that hypothesis 3 is not confirmed. In this study, general attitudes toward AI do not explain whether AI decisions are accepted. The regression model is not significant ($F(1,53) = 0.001$; $p = 0.972$). The explained variance is practically zero ($R^2 = 0.000$). Even if participants generally evaluate AI positively, this does not automatically increase acceptance of AI-supported consulting in this context. This observation is consistent with established acceptance models. Davis (1987) describes in the Technology Acceptance Model that usage and acceptance do not depend solely on a general attitude. The study of Merriman et al. (2024) found a positive correlation between AI affinity and the use of digital services, while other studies recent work demonstrates that this effect diminishes or disappears in sensitive areas, like financial or insurance decisions. They are strongly influenced by the specific situation as well as by perceived usefulness and perceived ease of use.

Venkatesh et al. (2003) shows that technology acceptance depends on various factors. Contextual conditions play a central role in this. For the study, this means, a general affinity for technology or AI is not sufficient. The decision-making situation is perceived as riskier and more important. Gen Z literature also supports this interpretation. Dewalska-Opitek et al. (2024) show that although Gen Z is generally open to AI, trust and acceptance depend heavily on the context of application. Kacperska et al. (2024) also argue that Gen Z does not evaluate AI across the board, but rather based on perceived consequences, risks, and fairness. This fits with the logic of the study: Gen Z may find AI interesting or helpful in everyday life, but still expects more control, better transparency, and clear accountability when it comes to insurance decisions.

6 Strategic recommendations for action

The results of this study suggest that hybrid consulting formats in the insurance sector offer Gen Z clear advantages over exclusively AI-supported consulting. This is most visible in transparency/comprehensibility and responsibility attribution: AI-only receives the lowest ratings, whereas hybrid and human consulting score significantly higher. In addition, the regression results indicate that loyalty is primarily driven by trust and perceived responsibility, while transparency tends to affect loyalty more indirectly. Overall, the findings imply that AI may increase efficiency, but Gen Z still expects traceable recommendations and a clearly identifiable person of responsibility when making insurance decisions. This aligns with prior research describing Gen Z's preference for efficient digital processes combined with human oversight in complex or risky contexts ("fast orientation, deep dive only on demand") (Cinar & Wollermann, 2024; Miller, 2025; Rapp & Réthy-Jensen, 2023). The relevance of these results is particularly strong in insurance because it is an intangible service: customers essentially buy a promise for the future that often proves its value only in a claim situation (Eickenberg, 2022). At the same time, insurance decisions can have long-term financial consequences and are therefore perceived as risky, even if the digital process itself appears quick and easy (EIOPA, 2024; Miller, 2025).

In this setting, it becomes crucial to understand why a product is recommended and who is responsible if uncertainties arise. This is exactly where AI-only shows weaknesses in the study: the decision-making process is rated as less comprehensible ($M = 3.83$) and the involvement of a responsible person is perceived as particularly low ($M = 2.78$). Against this backdrop, a two-stage hybrid consulting model is a plausible recommendation, as it fits Gen Z's communication preferences while addressing the insurance-specific need for clarity, security, and accountability (Dennstedt & Targan, 2025; EIOPA, 2024; Miller, 2025).

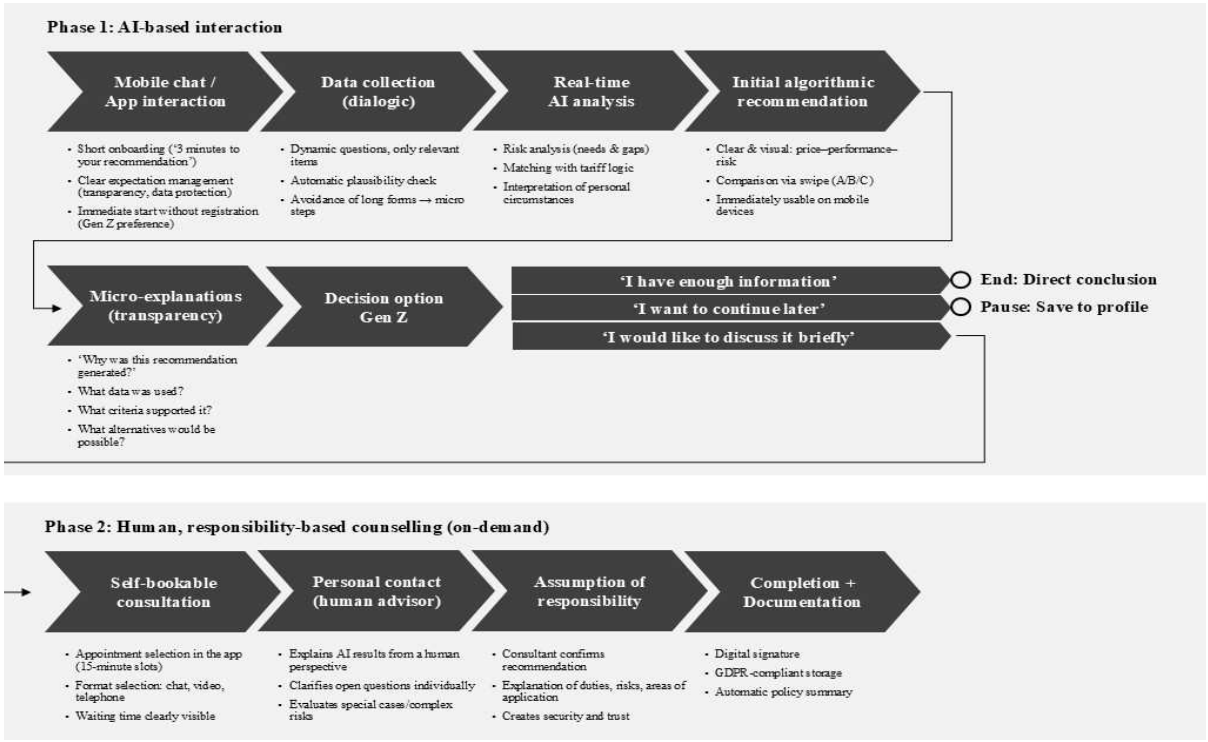

Figure 7: Strategic recommendations for Insurances[10]

Figure 7 outlines a two-stage hybrid model for insurance consulting. **In Phase 1**, customers enter relevant information via an app or web portal and receive an AI-generated initial recommendation. The study results indicate that this recommendation must not appear as a "black box," since AI-only shows the weakest process traceability (M = 3.83). Therefore, the recommendation should always be accompanied by short, easy-to-understand explanations (why this recommendation, which criteria were decisive, and which data were used). Research suggests that algorithmic decisions without explanatory logic are quickly perceived as non-transparent, and missing explainability strengthens black-box perceptions (Hersch et al., 2022; Kern & Loh, 2024). In addition, simple "what-if" functions (adjusting parameters and showing alternatives) can address the need for control and increase traceability, which is considered effective in XAI research (Shin, 2021; Zhou et al., 2021). This is also practical because insurance decisions are often made iteratively: customers typically compare options before committing, and transparent digital support can strengthen this phase (Bughin et al., 2017; Candreia et al., 2024).

Phase 2 is not meant to repeat standard information, but to clarify uncertainties, assess special cases, and make responsibility visible. This is critical because responsibility shows the strongest

[10] Recommendations for action are based on personal experience and observations.

scenario difference in the study ($\eta^2 = .20$), and AI-only is rated particularly low when no responsible person is identifiable ($M = 2.78$). In insurance, this matters because in the event of a claim or dispute, accountability cannot rest with "technology," but must be clearly assignable to an organization or person; unclear responsibility can therefore reduce perceived decision security (Eickenberg, 2022; EIOPA, 2024). A human advisor should accordingly serve as a clearly designated contact person who contextualizes the AI recommendation, answers individual questions, and assumes responsibility when needed. This approach is in line with models of human-AI collaboration, according to which acceptance depends heavily on whether responsibility and accountability are clearly defined and visible (Do Khac & Leyer, 2025; Heyder et al., 2023). For Gen Z, this phase should be flexible to book (short slots, free choice of channel), because the literature describes self-control and low interaction barriers as key expectations (Cinar & Wollermann, 2024; Miller, 2025; Rapp & Réthy-Jensen, 2023). In addition, the human phase can perform a quality function that is important in the insurance context: it can check whether there are any special cases, whether important information is missing, or whether risks have been incorrectly assessed. This not only creates a greater "sense of security," but also provides realistic technical assurance for the decision, which purely digital systems are often unable to provide in full (Do Khac & Leyer, 2025; EIOPA, 2024).

7 Conclusion and Outlook

7.1 Limitation

This study provides valuable insights into how participants perceive human, AI-based, and hybrid consulting scenarios. However, several limitations related to design, methodology, and content must be considered. First, the study is cross-sectional and therefore captures attitudes and perceptions at only one point in time. A longitudinal approach would be better suited to observe how trust, responsibility attribution, and acceptance develop over repeated or real interactions with AI-based consulting. Second, the study focuses strongly on subjective perceptions. All constructs (trust, transparency, responsibility attribution, loyalty intentions, and AI attitudes) were measured through self-reports. This means the study reflects perceived evaluations in a hypothetical situation rather than objective behavior. Self-reports can also be biased, for example by response tendencies. Third, the design is scenario-based and text-driven. Participants did not experience an actual interaction with a consultant or a system. In real decision contexts, factors such as, time pressure, or system performance could influence participants. Fourth, the use of a non-probabilistic convenience sample limits generalizability. Recruitment via social media and snowball sampling is efficient for reaching Gen Z, but it may produce a self-selective sample that differs from the broader German Gen Z population. Fifth, the study deliberately treats insurance consulting at a general level and does not differentiate between insurance lines. This was necessary for comparability across scenarios, but it limits transferability because expectations, risk perception, and information needs can vary by product type. A further methodological limitation concerns scenario recognition. Scenario assignment was checked with manipulation/control questions. A small number of respondents could not clearly be assigned to one of the scenarios and were therefore stored as “no clear assignment” in SPSS. This category does not represent an additional experimental condition, but when included in omnibus analyses it leads to four-group ANOVA outputs and different degrees of freedom. The main interpretation therefore relies on the three intended scenarios and planned comparisons between AI-only and hybrid consulting. Finally, the sample size restricts the use of more complex statistical models. Although more advanced modeling could provide deeper insights into mechanisms and interaction effects, it would have limited reliability given the available cases. Therefore, the study focuses on correlations and relatively simple regressions. Overall, these limitations do not reduce the relevance of the findings, but they indicate that the study is exploratory and conducted under controlled conditions. The results should be understood as theoretically grounded empirical evidence and as a basis for future research.

7.2 Final Considerations

In conclusion, this master's thesis shows how sensitive Gen Z is to the design of AI-supported advice in the insurance context. The results make it clear that it is not the use of AI itself that determines acceptance, but above all the question of whether recommendations appear comprehensible and whether responsibility can be clearly assigned. This is precisely where the weaknesses of purely AI-based advice lie: if the decision-making process is perceived as difficult to understand and no responsible authority is identifiable, the perceived certainty of the decision decreases, a critical point in a market where services are intangible and trust is considered the central basis for long-term customer relationships (Eickenberg, 2022; Morgan & Hunt, 1994). At the same time, the study makes it clear that hybrid formats have the potential to combine the advantages of both worlds: AI can offer quick orientation and efficiency, while humans act as anchors of explanation and responsibility. This makes a hybrid approach plausible not only technologically, but above all psychologically and organizationally. Particularly relevant here is the finding that loyalty in this study is primarily explained by trust and attribution of responsibility. In practice, this means that insurers who want to win over Gen Z in the long term should not view digital consulting exclusively as an automation project, but rather as a design task in which transparency, control options, and clear responsibilities are systematically taken into account. Despite the limitations, in particular the scenario-based design and self-reported data, the results provide reliable guidance on which factors are particularly important to Gen Z in the AI-supported advisory experience. Overall, the work underscores that the future of insurance advice is likely to be neither purely human nor purely algorithmic but rather lies where digital efficiency and human responsibility are brought together in a transparent, trustworthy process.

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List of Appendices

Appendix

Equation 1: Questionnaire[12]

Hybrid Human - AI Consulting Models in Insurance (Gen Z Study)

Start: Introduction & Declaration of Consent

Intro: This study examines how Gen Z interprets and responds to advice from humans and artificial intelligence (AI) in the context of the insurance industry. There are no right or wrong answers; what matters is your personal assessment. The survey takes about 5-8 minutes. Your information will remain anonymous and will be used exclusively for scientific purposes. By clicking 'Continue', you agree to participate.

Start: Block 15

Info **Short introduction:** This survey focuses on how young adults perceive advice from people, artificial intelligence (AI) or a combination of both in the insurance sector.
At the beginning, you will be presented with a brief **scenario** describing a possible **advisory situation**. All of the following questions **relate to this scenario** and **your personal assessment**.
Please consider the scenario in each answer to provide as accurate a picture of your perception as possible.

S1 **Scenario: Consultation with a human insurance advisor** You would like to take out a new insurance policy. To do so, you make an appointment with an **insurance advisor**. At the beginning, the advisor asks you for personal information (e.g. age, income, life situation, desired insurance coverage). Based on this information, they explain the various tariff options and their differences in price, benefits and excess. The recommendation is based solely on the advisor's experience and expertise. During the conversation, it is pointed out that your information will be treated confidentially and used for advisory purposes only. You can ask at any time what information is being stored and request that it be deleted. At the end, the advisor will make a recommendation and explain in a comprehensible manner why this tariff is best suited to you. Please imagine that you have experienced this consultation and then evaluate your impressions.

S2 **Scenario: Advice from an AI** You want to take out a new insurance policy. The insurance company offers fully automated online advice based on **artificial intelligence (AI).** You enter your personal details (e.g. age, income, life situation, desired insurance cover).

The system analyses your information, compares it with anonymized customer data and displays several tariffs with brief explanations, e.g. 'This option offers the best value for money for your profile.' The system informs you that your data will be processed in encrypted form, will not be passed on to third parties and will be used exclusively for calculating the offer. You can check which information has been stored at any time and delete it.

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[12] The questionnaire was imported and embedded using Qualtrics' original format. Because the instrument was transferred via the platform, exact formatting cannot be guaranteed to be preserved in all cases.

No human advisor is involved. At the end, the AI shows you a recommendation that you can accept or adjust directly. Please imagine that you have experienced this consultation and then evaluate it.

S3 **Scenario: Advice from a human insurance advisor and an AI**. You want to take out a new insurance policy. On the insurance company's website, you **start** with an initial digital consultation with a c**hatbot based on artificial intelligence (AI).**

The chatbot asks you questions about your age, income, life situation and desired insurance coverage. Based on your input, the system analyses the data and generates an initial tariff recommendation with a brief explanation, e.g.: 'This option offers the best value for money for your profile.'

After the automated consultation is complete, an **insurance advisor takes over.** The advisor checks the AI recommendation, explains in understandable terms how it was arrived at and adds their personal assessment, e.g. whether additional benefits would be useful or whether the tariff should be adjusted. Both the AI and the advisor pay attention to data protection and confidentiality: your details are stored in encrypted form, are not passed on to third parties and are only used for advisory purposes. If you wish, you can view which data has been stored and request its deletion.

At the end, **the chatbot and advisor jointly make a recommendation**, with the advisor bearing the final responsibility.

Please imagine that you have experienced this consultation and then evaluate your impressions.

Transparency and traceability of the recommendation

B2 **Perceived transparency**. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

Equation 2: Transparency and traceability of the recommendation

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I understand how the recommended insurance contract came about. (1)	○	○	○	○	○	○	○
The advice was clear and transparent. (2)	○	○	○	○	○	○	○
I know what data and criteria the	○	○	○	○	○	○	○

recommendation is based on. (3)							
I believe that the decision was made fairly. (4)	○	○	○	○	○	○	○

Equation 3: Assignment of responsibility

Attribution of responsibility

B3 **Allocation of responsibilities.** Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I understand perfectly well who is responsible for the final recommendation. (1)	○	○	○	○	○	○	○
I trust that a responsible person is involved in this process. (2)	○	○	○	○	○	○	○
I believe that responsibility has been appropriately distributed/assigned. (3)	○	○	○	○	○	○	○

Equation 4: Trust in the advisor

Trust

Diese Frage anzeigen:

If S1 Angezeigt

Or Or S3 Angezeigt

B4 **Trust in the advisor**. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
The advisor appears competent and professionally qualified. (1)	○	○	○	○	○	○	○
I believe that he/she is acting in my best interests. (2)	○	○	○	○	○	○	○
I consider him/her to be honest and reliable. (3)	○	○	○	○	○	○	○

Equation 5: Trust in AI

b) Trust

Diese Frage anzeigen:

If S2 Angezeigt

Or Or S3 Angezeigt

B4 **Trust in AI**. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
The system provides objective and accurate recommendations. (1)	○	○	○	○	○	○	○
I consider the AI to be reliable. (2)	○	○	○	○	○	○	○
I trust that the AI makes fair decisions. (3)	○	○	○	○	○	○	○

Equation 6: Trust in the insurance company as an organization

c) Trust

Diese Frage anzeigen:

If S1 Angezeigt

Or Or S2 Angezeigt

Or Or S3 Angezeigt

B4 Trust in the insurance company as an organization

Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

Diese Antwortmöglichkeit anzeigen:

If S2 Angezeigt

Or Or S3 Angezeigt

Diese Antwortmöglichkeit anzeigen:

If S1 Angezeigt

Or Or S3 Angezeigt

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I have confidence in the insurance company as a business. (1)	○	○	○	○	○	○	○
Diese Antwortmöglichkeit anzeigen: *If S2 Angezeigt* *Or Or S3 Angezeigt* I believe that the company uses AI responsibly. (2)	○	○	○	○	○	○	○
Diese Antwortmöglichkeit anzeigen: *If S1 Angezeigt* *Or Or S3 Angezeigt* I believe that the company trains its employees well to make responsible and informed recommendations. (4)	○	○	○	○	○	○	○
The company appears to be ethical and transparent to me. (3)	○	○	○	○	○	○	○

Equation 7: Perceived quality of advice

Perceived quality of advice

B6 Assessment of the advice. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
This type of advice helped me make the right decision. (1)	○	○	○	○	○	○	○
This type of adice makes the decision-making process easier and more efficient. (2)	○	○	○	○	○	○	○
I would use this form of advice again in the future (3)	○	○	○	○	○	○	○
I would recommend this form of advice to friends. (4)	○	○	○	○	○	○	○

Equation 8: Transparent communication and traceability

Transparent communication and traceability

B7 **Transparent communication and traceability.** Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I have the impression that the provider handles my personal data responsibly (data protection). (1)	○	○	○	○	○	○	○
I felt that all important information was communicated to me openly. (2)	○	○	○	○	○	○	○
I could understand how the recommendation came about. (3)	○	○	○	○	○	○	○
The provider gives the impression of handling new technologies (AI) responsibly and in compliance with regulations. (4)	○	○	○	○	○	○	○

Equation 9: Loyalty to the company

Loyalty to the company

B8 **Feedback on the insurance company.** Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I would take out insurance with this provider again in the future. (1)	○	○	○	○	○	○	○
I would prefer this provider, even if others offer slightly cheaper deals. (2)	○	○	○	○	○	○	○
I see this provider as a long-term partner for insurance matters. (3)	○	○	○	○	○	○	○
I feel that this provider really understands my needs. (4)	○	○	○	○	○	○	○

Equation 10: Acceptance of AI decisions

Acceptance of AI decisions

B5 **Acceptance of AI decisions**. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

Showing answer:: If S2 Angezeigt Or Or S3 Angezeigt

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
Showing answer:: If S2 Angezeigt Or Or S3 Angezeigt I feel uncomfortable when AI decides on insurance matters. (1)	○	○	○	○	○	○	○
I prefer human assessments to AI recommendations. (2)	○	○	○	○	○	○	○
If AI delivers good results, I trust it in the long term. (3)	○	○	○	○	○	○	○
I would feel more comfortable if AI decisions were reviewed by a person. (4)	○	○	○	○	○	○	○

Equation 11: Attitude toward AI

Attitude toward AI

B9 **Personal attitude towards AI**. Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I find it exciting when AI is used in everyday life. (1)	○	○	○	○	○	○	○
I feel comfortable when AI supports decisions that affect me. (3)	○	○	○	○	○	○	○
I see AI as an opportunity rather than a risk. (2)	○	○	○	○	○	○	○
I think it's good when companies use AI for consulting to make the process more efficient. (4)	○	○	○	○	○	○	○

Demographics

B10 Age: Freetext

B10 Gender:

- ○ female (1)
- ○ male (2)
- ○ diverse (3)

B10 Level of education:

- ○ Highschool or less (1)
- ○ Bachelor's degree (2)
- ○ Master's degree (3)
- ○ other (4)

B10 Experience with insurance:

- ○ 1-2 policies (1)
- ○ 3+ policies (2)
- ○ don't know (3)
- ○ none (4)
- ○ no informations (5)

B10 Experience with AI systems:

- ○ occasionally (1)
- ○ regulary (2)
- ○ none (3)

B10 **Trust in digital services in general:** Please respond to all the statements below on a scale of 1-7 (scale: 1 = strongly disagree, 7 = strongly agree).

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)
I generally trust digital applications. (1)	○	○	○	○	○	○	○

Block 16

Q22 Thank you for participating in the survey. Your responses will be included anonymously in my master's thesis: 'Hybrid human-AI consulting models in the insurance industry: Effects on trust, transparency and customer loyalty – with a focus on Gen Z' If you have any questions, please feel free to contact me by email at s-tschlicht@ucp.pt.

Thank you for taking the time to share your opinion.

Equation 12: Hypotheses 1 Testing

T-Test for Transparency

T-Test

Group Statistics

	Szenario	N	Mean	Std. Deviation	Std. Error Mean
Transparency_mean	AI Consulting	23	4,6196	1,41395	,29483
	Hybrid Consulting	37	5,5135	1,25685	,20662

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Transparency_mean	Equal variances assumed	-2,553	58	,007	,013	-,89395	,35014	-1,59483	-,19307
	Equal variances not assumed	-2,483	42,633	,009	,017	-,89395	,36003	-1,62019	-,16771

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Transparency_mean	Cohen's d	1,31865	-,678	-1,210	-,140
	Hedges' correction	1,33601	-,669	-1,194	-,139
	Glass's delta	1,25685	-,711	-1,252	-,161

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

T-Test for Responsibility

T-Test

Group Statistics

	Szenario	N	Mean	Std. Deviation	Std. Error Mean
Responsibility_mean	AI Consulting	23	3,5652	1,39420	,29071
	Hybrid Consulting	37	5,1081	1,31716	,21654

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Responsibility_mean	Equal variances assumed	-4,314	58	<,001	<,001	-1,54289	,35764	-2,25878	-,82700
	Equal variances not assumed	-4,256	44,764	<,001	<,001	-1,54289	,36249	-2,27310	-,81268

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Responsibility_mean	Cohen's d	1,34690	-1,146	-1,702	-,581
	Hedges' correction	1,36463	-1,131	-1,680	-,573
	Glass's delta	1,31716	-1,171	-1,751	-,579

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

T-Test for Trust

T-Test

Group Statistics

	Szenario	N	Mean	Std. Deviation	Std. Error Mean
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	AI Consulting	22	4,5455	1,31151	,27961
	Hybrid Consulting	28	4,9286	,95304	,18011

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Equal variances assumed	-1,196	48	,119	,237	-,38312	,32024	-1,02700	,26076
	Equal variances not assumed	-1,152	37,077	,128	,257	-,38312	,33260	-1,05698	,29075

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Cohen's d	1,12403	-,341	-,902	,223
	Hedges' correction	1,14198	-,335	-,887	,220
	Glass's delta	,95304	-,402	-,967	,170

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Descriptives table of the one-way ANOVA for Trust and Responsibility

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	no clear assignment	0	.	.	.	.	.	.	.
	Human Consulting	22	5,2576	1,05375	,22466	4,7904	5,7248	2,00	7,00
	AI Consulting	22	4,5455	1,31151	,27961	3,9640	5,1269	1,00	6,67
	Hybrid Consulting	28	4,9286	,95304	,18011	4,5590	5,2981	2,67	6,33
	Total	72	4,9120	1,12309	,13236	4,6481	5,1759	1,00	7,00
Responsibility_mean	no clear assignment	5	4,0000	1,98606	,88819	1,5340	6,4660	2,00	6,67
	Human Consulting	24	5,2222	1,55002	,31640	4,5677	5,8767	1,00	7,00
	AI Consulting	23	3,5652	1,39420	,29071	2,9623	4,1681	1,00	6,67
	Hybrid Consulting	37	5,1081	1,31716	,21654	4,6689	5,5473	2,00	7,00
	Total	89	4,6779	1,58469	,16798	4,3441	5,0117	1,00	7,00

One-way ANOVA for Trust and Responsibility

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Between Groups	5,591	2	2,795	2,297	,108
	Within Groups	83,963	69	1,217		
	Total	89,554	71			
Responsibility_mean	Between Groups	44,732	3	14,911	7,191	<,001
	Within Groups	176,257	85	2,074		
	Total	220,989	88			

Descriptives table of the one-way ANOVA for Transparency

Oneway

Descriptives

Transparency_mean

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
no clear assignment	5	4,6000	1,54717	,69192	2,6789	6,5211	3,25	7,00
Human Consulting	24	5,3854	1,32283	,27002	4,8268	5,9440	2,25	7,00
AI Consulting	23	4,6196	1,41395	,29483	4,0081	5,2310	1,50	6,50
Hybrid Consulting	37	5,5135	1,25685	,20662	5,0945	5,9326	1,50	7,00
Total	89	5,1966	1,36799	,14501	4,9085	5,4848	1,50	7,00

One-way ANOVA for Transparency

ANOVA

Transparency_mean

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	14,010	3	4,670	2,634	,055
Within Groups	150,674	85	1,773		
Total	164,684	88			

Equation 13: Hypotheses 2 Testing

Correlation between Loyality, Trust, Responsibility and Transparency

Correlations

Correlations

		Loyality_mean	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Responsibility_mean	Transparency_mean
Loyality_mean	Pearson Correlation	1	,605***	,597***	,583***
	Sig. (2-tailed)		<,001	<,001	<,001
	N	89	72	89	89
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Pearson Correlation	,605***	1	,444***	,565***
	Sig. (2-tailed)	<,001		<,001	<,001
	N	72	72	72	72
Responsibility_mean	Pearson Correlation	,597***	,444***	1	,692***
	Sig. (2-tailed)	<,001	<,001		<,001
	N	89	72	89	89
Transparency_mean	Pearson Correlation	,583***	,565***	,692***	1
	Sig. (2-tailed)	<,001	<,001	<,001	
	N	89	72	89	89

***. Correlation at 0.001(2-tailed)

Multiple Regression

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
Loyality_mean	4,4722	1,21649	72
alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	4,9120	1,12309	72
Transparency_mean	5,2708	1,31871	72
Responsibility_mean	4,7917	1,60344	72

Correlations

		Loyality_mean	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Transparency_mean	Responsibility_mean
Pearson Correlation	Loyality_mean	1,000	,605	,594	,578
	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	,605	1,000	,565	,444
	Transparency_mean	,594	,565	1,000	,660
	Responsibility_mean	,578	,444	,660	1,000
Sig. (1-tailed)	Loyality_mean	.	<,001	<,001	<,001
	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	,000	.	,000	,000
	Transparency_mean	,000	,000	.	,000
	Responsibility_mean	,000	,000	,000	.
N	Loyality_mean	72	72	72	72
	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	72	72	72	72
	Transparency_mean	72	72	72	72
	Responsibility_mean	72	72	72	72

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,710[a]	,504	,482	,87520

a. Predictors: (Constant), Responsibility_mean, alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios, Transparency_mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	52,983	3	17,661	23,057	<,001[b]
	Residual	52,086	68	,766		
	Total	105,069	71			

a. Dependent Variable: Loyality_mean

b. Predictors: (Constant), Responsibility_mean, alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios, Transparency_mean

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	,521	,504		1,034	,305	-,485	1,527		
	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	,397	,113	,367	3,522	<,001	,172	,622	,672	1,488
	Transparency_mean	,183	,115	,199	1,598	,115	-,046	,412	,472	2,119
	Responsibility_mean	,216	,087	,284	2,484	,015	,042	,389	,556	1,797

a. Dependent Variable: Loyality_mean

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	alle 3 zsmf. Trust Variablen unter der Bedingung der Szenarios	Transparency_mean	Responsibility_mean
1	1	3,899	1,000	,00	,00	,00	,00
	2	,056	8,357	,21	,06	,00	,59
	3	,025	12,533	,78	,51	,10	,13
	4	,020	14,007	,00	,42	,89	,27

a. Dependent Variable: Loyality_mean

Equation 14: Hypotheses 3 Testing

Correlation between general attitudes toward AI and acceptance of AI decisions

Correlations

Correlations

		KI_Attitude_mean	KI_Acceptance_mean
KI_Attitude_mean	Pearson Correlation	1	-,005
	Sig. (2-tailed)		,972
	N	60	55
KI_Acceptance_mean	Pearson Correlation	-,005	1
	Sig. (2-tailed)	,972	
	N	55	55

Linear Regression between KI Acceptance and KI Attitude

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
KI_Acceptance_mean	4,7727	1,07827	55
KI_Attitude_mean	5,4045	1,34671	55

Correlations

		KI_Acceptance_mean	KI_Attitude_mean
Pearson Correlation	KI_Acceptance_mean	1,000	-,005
	KI_Attitude_mean	-,005	1,000
Sig. (1-tailed)	KI_Acceptance_mean	.	,486
	KI_Attitude_mean	,486	.
N	KI_Acceptance_mean	55	55
	KI_Attitude_mean	55	55

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,005[a]	,000	-,019	1,08838

a. Predictors: (Constant), KI_Attitude_mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,001	1	,001	,001	,972[b]
	Residual	62,783	53	1,185		
	Total	62,784	54			

a. Dependent Variable: KI_Acceptance_mean

b. Predictors: (Constant), KI_Attitude_mean

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	4,794	,612		7,830	<,001	3,566	6,022		
	KI_Attitude_mean	-,004	,110	-,005	-,035	,972	-,224	,217	1,000	1,000

a. Dependent Variable: KI_Acceptance_mean

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	KI_Attitude_mean
1	1	1,971	1,000	,01	,01
	2	,029	8,222	,99	,99

a. Dependent Variable: KI_Acceptance_mean