



The future of professional development: Adoption of AI-powered career platforms

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Abstract

As artificial intelligence enters increasingly personal aspects of life, this thesis explores its role in career development—specifically through AI-powered career coaching platforms. While traditional coaching methods are often costly, generic, or inaccessible, AI-based tools promise scalable, personalized guidance. However, adoption remains limited, particularly in trust-sensitive domains like career planning.

To investigate the factors that drive adoption and sustained engagement, this study applies an integrated framework combining the Technology Acceptance Model and the Diffusion of Innovation theory. A survey of 130 participants from German-speaking countries measured user traits, technology perceptions, and feature preferences. Both quantitative (regression analysis) and qualitative (thematic coding) methods were used.

The results show that perceived usefulness, trust in data handling, and explainable recommendations are the most influential predictors of adoption. Psychological readiness and familiarity with AI significantly outweigh demographic traits in shaping openness. Users primarily value operational features such as CV optimization and cover letter writing, while more strategic services are secondary.

These findings suggest that AI-career tools should focus on delivering early value, ensuring transparent data practices, and building user trust through explainability. The study offers practical guidance for platform providers and contributes new insights to technology acceptance research in private, emotionally complex domains.

Keywords: Artificial Intelligence, Career Guidance, Technology Acceptance, User Trust, Explainable AI

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Resumo

À medida que a inteligência artificial (IA) passa a integrar aspectos mais pessoais da vida, esta dissertação investiga o seu papel no desenvolvimento de carreira, com foco em plataformas de orientação profissional baseadas em IA. Embora os métodos tradicionais de coaching sejam frequentemente dispendiosos ou pouco personalizados, as soluções baseadas em IA prometem orientação escalável e adaptada. No entanto, a adoção continua limitada, especialmente em contextos sensíveis à confiança, como o planeamento de carreira.

Este estudo aplica uma abordagem teórica integrada, combinando o Modelo de Aceitação de Tecnologia com a Teoria da Difusão da Inovação. Um inquérito com 130 participantes de países de língua alemã avaliou características dos utilizadores, perceções tecnológicas e preferências de funcionalidades. Foram utilizadas análises quantitativas (regressão) e qualitativas (análise temática).

Os resultados indicam que a utilidade percebida, a confiança no tratamento de dados e a explicabilidade das recomendações são os principais preditores de adoção. A predisposição psicológica e a familiaridade com IA mostraram-se mais relevantes do que fatores demográficos. Funcionalidades práticas como otimização de CVs e apoio na redação de cartas de motivação foram as mais valorizadas.

Estes resultados sugerem que ferramentas baseadas em IA devem priorizar a criação de valor inicial, garantir práticas de dados transparentes e promover a confiança através da explicabilidade. O estudo fornece orientações práticas para o desenvolvimento de plataformas e contribui para a investigação sobre aceitação de tecnologia em domínios pessoais.

Palavras-chave: Inteligência Artificial, Orientação Profissional, Aceitação de Tecnologia, Confiança do Utilizador, IA Explicável

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When I submitted this thesis on May 25th, 2025, I couldn't have imagined—two years earlier—what a challenging, exciting, and deeply formative journey lay ahead. Throughout the Master's program, I've grown in more ways than I anticipated. I've acquired new knowledge, developed valuable skills, and, perhaps most importantly, built friendships that will stay with me for life. For all of this, I am truly grateful.

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This chapter of my life marks a personal milestone I'm proud of. From a small village in Southern Germany to graduating my Bachelor in Frankfurt and then moving to Lisbon to follow this path—I want to end with a note to myself: even in moments of doubt, I stayed the course. I made it. Anything is possible.

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List of Abbreviations

AI	Artificial Intelligence
TAM	Technology Acceptance Model
DOI	Diffusion of Innovation
CV	Curriculum Vitae
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
XAI	Explainable Artificial Intelligence
RQ	research questions
SD	standard deviations
VIF	Variance Inflation Factor
ANOVA	Analysis of Variance
SPSS	Statistical Package for the Social Sciences

1 Introduction

The rise of Artificial Intelligence (AI) in everyday applications has begun to reshape how individuals navigate personal and professional decisions. One particularly promising domain is career development, where AI-powered tools offer the potential to provide personalized guidance, increase access to support, and reduce the cost and time associated with traditional coaching services. As these technologies evolve, they hold the promise to democratize career planning and help individuals explore new paths with greater confidence and clarity. However, the introduction of AI into such personal and trust-sensitive domains also raises critical questions about user acceptance, data privacy, and the perceived credibility of algorithmic advice [1]. This thesis explores the conditions under which individuals are willing to adopt and continue using AI-powered career coaching tools, offering new insights into the psychological, functional, and trust-related factors that shape technology engagement in highly personal decision-making contexts. Beyond academic relevance, the study's findings offer practical implications for the development of new business models in the field of AI-powered career support.

1.1 The Business Idea

Entering the career development and job market landscape, the venture aims to introduce an AI-powered career coach that addresses the needs of individuals looking to transition into more fulfilling roles and those seeking to advance within their current careers. This tool leverages advanced artificial intelligence to provide personalized, actionable guidance tailored to each user's unique professional background, goals, and aspirations. The platform's primary objective is to empower users who feel dissatisfied or stagnant in their current employment by helping them identify viable career paths, as well as offering strategies for career advancement for professionals eager to climb the corporate ladder.

In its initial version, the AI career tool is designed to provide users with alternative job recommendations that better align with their values, interests, and desired work environments. Rather than offering generic listings, the platform intelligently matches users with roles in which they are more likely to feel fulfilled and motivated. The aim is to support individuals who feel dissatisfied in their current jobs by helping them discover career paths where they could thrive. In the long term, the tool is envisioned to evolve into a full-spectrum career coach, capable of guiding users through every stage of their professional development—from exploring new opportunities

to preparing for interviews, negotiating offers, and planning long-term growth.

This platform called My-Career-Coach.com operates as a two-sided platform. On one side, it's completely free for users who are open to exploring new careers or industries. These jobseekers receive guidance from the platform, helping them understand which fields might be a good fit and matching them to relevant openings. On the other side, companies that welcome candidates from diverse backgrounds pay a fee to post their positions. Just like Indeed or StepStone, this fee-based model keeps the service free for users. However, My-Career-Coach.com goes a step further by actively advising and matching unhappy or uncertain workers with compatible roles in new industries. In future, it might be interesting to introduce a premium subscription option that offers extra benefits such as personalized Curriculum Vitae (CV) or cover letter support.

1.2 Value Proposition

The product, My-Career-Coach.com, helps users who want either to take the next step in their career or transition into a new industry by reducing the typical time and cost associated with career guidance. It offers free, 24/7 career coaching, including job matching.

Unlike human career coaches who may charge around 200€ per hour, governmental institutions that are not powered by artificial intelligence, or other AI-based career platforms that aren't matching people with open positions, My-Career-Coach.com provides an end-to-end solution for seamless career progression [2]. Different to the competition, the service is completely free for job seekers. In our business model, companies will finance the service by being able to advertise their open job positions for a monthly fee.

1.3 Problem Statement & Relevance

In today's rapidly evolving job market, many individuals find themselves in roles that no longer offer personal fulfilment, development, or alignment with their evolving aspirations [3]. Yet exploring alternative career paths, especially across industries, remains a complex and often overwhelming process. Traditional career guidance solutions, whether delivered through private coaching, public agencies, or internal mentoring, are often costly, time-limited, and insufficiently tailored to individual needs.

At the same time, recent advancements in artificial intelligence have demonstrated significant potential in automating and personalizing services across professional domains such as health-care, finance, and education [4] [5]. AI-driven job-matching tools, in particular, can process user data, skill profiles, and labor market dynamics to generate highly targeted career recom-

mentations. However, while academic research has examined AI acceptance in structured, task-oriented domains, the role of AI in deeply personal contexts—such as career decision-making—remains largely underexplored.

This thesis addresses that gap by investigating how individuals respond to AI-based career guidance. Specifically, it examines whether users are willing to consider AI-generated job suggestions when navigating professional transitions, and which psychological and functional factors drive their openness and long-term engagement. By doing so, this study contributes to a more nuanced understanding of how human–AI collaboration can unfold in private, trust-sensitive domains and offers a first step toward grounding these developments in user-centered evidence.

1.4 Research Questions

Understanding the conditions under which individuals are willing to adopt AI-powered career guidance tools is essential for designing digital platforms that are both effective and trusted. This becomes particularly relevant as career transitions become more frequent and individuals seek flexible, low-barrier alternatives to traditional coaching services. While AI has already transformed various professional sectors, its role in personal, trust-sensitive domains like career decision-making remains underexplored. This leads to the following research questions (RQ):

RQ1: *Who are the most likely early adopters of an online cross-industry career guidance platform such as My-Career-Coach.com?*

RQ2: *Which specific user acceptance factors most strongly influence the adoption of AI-powered career coaching?*

RQ3: *Which specific perceived benefits are most correlated with long-term engagement in AI-driven career coaching?*

To answer these questions, the thesis first explores the current landscape of AI adoption in career services, along with psychological and technological factors that influence user trust and openness. It then introduces the theoretical foundation by combining the Technology Acceptance Model (TAM) and Diffusion of Innovation (DOI) theory to explain individual decision-making and innovation uptake. The subsequent methodology chapter outlines the survey design, data collection and analytical approach. This is followed by a results and discussion section that presents both quantitative and qualitative findings. Finally, the thesis concludes by summarizing the main findings, highlighting academic and managerial implications, discussing limitations, and proposing directions for future research.

2 Literature Review

2.1 Career Coaching and Job-Matching Platforms

Job-matching websites and career coaching are essential resources to support people in their career transitions. Career guidance has traditionally been delivered by human career coaches, government job agencies, and other job search websites. Although these traditional approaches have assisted job seekers, they have crucial limitations like high costs, accessibility, and personalization. More recently, AI has become a potentially transformative tool to improve career coaching by providing personalized, scalable, and data-driven recommendations.

2.1.1 Traditional Career Coaching and Job-Matching Services

Conventional career coaching typically requires one-on-one interaction between clients and professional career counselors who provide guidance on career planning, job hunting, and skills development. Career coaches may be independent or employed by state-sponsored employment agencies. For example, in Germany, the “Agentur für Arbeit” provides free career guidance and job placement services. The purpose of these services is to support individuals seeking employment, yet they are plagued by issues like extensive waitlists, bureaucratized and standardized advice, and limited resources [2].

At the same time, online employment matching websites such as LinkedIn, Indeed, and StepStone have become central to matching job seekers with employers. These websites allow users to search for job openings, network with professionals in their field, and apply for jobs [6]. However, their main function is as job depositories more than as personalized career advisory services. Individuals are usually navigating dozens of job ads without being provided with personalized advice regarding which positions are most appropriate for their abilities, interests, and career aspirations [7].

Despite their popularity, both conventional career coaching and career-matching sites suffer from a variety of limitations that can diminish their usefulness. According to Indeed.com [8], one-on-one career guidance services tend to be expensive and thus remain out of reach for a large segment of the labor force. On the other hand, career services provided by government agencies, although free or low-cost, tend to present general advice that may not be relevant to an individual’s unique career goals or personal aptitudes. Furthermore, the majority of job-matching sites

play a passive role in that they need users to undertake manual search and filtering of available jobs instead of making proactive and personalized suggestions about their professional experience, competence, and career aspirations. Consequently, most job seekers experience challenges in terms of realizing appropriate career trajectories or shifting to other sectors, thereby calling for more advanced and personalized career guidance tools [9].

The limitations of high costs, low personalization, and labor-intensive processes indicate the necessity of more effective career guidance methods. As the next section will illustrate, recent AI advancements present a possible solution by delivering scalable, personalized coaching services to large segments of job seekers.

2.1.2 AI-Powered Coaching

AI-powered coaching has emerged as a transformative method in both professional and personal development. Unlike human coaches, AI systems offer continuous availability, scalability, and cost-efficiency [10]. Drawing on machine learning algorithms, these tools personalize feedback and guidance and are used in leadership training, sales performance, mental health support, and skill development. Research indicates that structured goal attainment processes can benefit from AI generated recommendations, leading to enhanced engagement and learning outcomes [11].

Compared to human trainers, AI processes are less subjective, adapting in real time based on industry trends and predictive analytics. Research supports the fact that AI is most well-suited for repetitive or formalized coaching contexts that call for instant feedback and continuous progress monitoring [12]. For instance, AI-driven sales training has elevated worker performance through scenario-based suggestions. These observations point toward AI's potential in contexts aimed at skill development and quantifiable guidance.

Yet, trust and transparency remain at the forefront of issues. Users may doubt AI-generated recommendations in situations requiring emotional intelligence or close human relationships. Some studies further add that AI works best when coupled with human oversight, blending data-informed guidance with compassion [11]. Furthermore, explainability fosters greater trust by clarifying how suggestions are generated [13]. This hints to the point of not only presenting users' results, but also why these results make sense in their case.

Although AI-driven coaching tackles many limitations of traditional services, its adoption ultimately depends on user trust and acceptance. The next section examines critical factors that influence AI adoption, such as trust, resistance to automation, and privacy.

2.2 AI Adoption and User Trust

Artificial intelligence utilization has quickly spread across professional services, driving fundamental transformation throughout healthcare, finance, and education sectors. AI technology is being applied more in automating decisions, augmenting operational effectiveness, and amplifying personalization efforts.

2.2.1 Artificial Intelligence

AI refers to a wide range of technologies that allow machines to simulate mental processes like those of human beings, including learning, problem-solving, and decision-making. AI technologies are based on extensive datasets, pattern recognition, and predictive analytics to execute tasks that formerly needed human intelligence. AI is applied in business and professional services for automating intricate operations, enhancing efficiency, and enhancing the quality of decision-making. Artificial intelligence has been widely adopted in fields including marketing, finance, and operations, where machine learning algorithms are applied to large datasets to derive conclusions and make recommendations [14]. Organizations which deliberately integrate artificial intelligence into their business models achieve competitive edge through efficiency improvement and innovation [5].

However, in this context, acceptance of artificial intelligence is frequently accompanied by scepticism out of worries of trust, aversion to automation, and data safety issues. It is crucial in the assessment of user interactions with AI tools, e.g., coaching software [4], to comprehend what drives the acceptance of AI. Some industries are faster in adapting AI, from which slower-adapting services can learn about their adapting behaviour.

2.2.2 AI Adoption in Professional Services

Artificial Intelligence is increasingly being used in professional services, demonstrating its potential to speed up productivity and improve decision-making. In medicine, AI-powered diagnostic tools are implemented to more precisely diagnose disease than conventional techniques, while predictive analytics are utilized to individualize the treatment strategy. Research has shown that AI-powered models employed for radiology and pathology have the potential to considerably improve diagnostic quality, thereby minimizing human error [15]. In finance, AI is being utilized to identify fraud, analyze risks, and robotize customer support. AI-powered chatbots and robo-advisors give financial counsel reliant on real-time market information and client behavior. In education, on the other hand, AI-powered tutoring programs personalize learning activities, modifying content based on individual students' needs [16].

Despite these advantages, the adoption of AI varies across industries. Finance and healthcare have embraced AI quickly owing to evident efficiency benefits, but education and career coaching continue to witness hurdles because of user acceptance and perceived trustworthiness. It has been researched that workers in trust-sensitive sectors are more reserved in embracing AI solutions because of issues regarding algorithmic bias along with ethical concerns [12].

2.2.3 Psychological Barriers to AI Adoption

Although AI offers increased efficiency and scalability, users often hesitate to fully trust AI-driven recommendations. Psychological barriers to AI adoption can be categorized into the following three primary concerns in trust, resistance to automation and data privacy concerns.

Trust and Explainability

Among the greatest barriers to artificial intelligence adoption is the lack of trust. Users tend to doubt the validity of recommendations provided by AI over those provided by human experts. Research suggests that when AI systems are not transparent, users cannot comprehend the rationale for automated decisions, hence generating scepticism [17]. To resolve this challenge, Explainable Artificial Intelligence (XAI) models have been programmed to elaborate the rationale for AI-generated recommendations, with the goal of enhancing trust and fostering adoption.

Explainable AI relies on the principle that humans will trust more in AI-driven recommendations if they understand the rationale behind them [18]. From a technical perspective, XAI entails a set of methodologies—such as model visualization and feature-attribution techniques—that translate complex algorithms into more interpretable outputs. Accordingly, an artificial intelligence coach can recognize the particular skill or experience of a given user that has the greatest influence on a given career recommendation, thereby allowing users to see the reasoning behind every recommendation. Such levels of transparency dismiss the "black box" phenomenon usually associated with machine learning, reduce fears by showing AI-driven decisions are founded on reasonable patterns rather than random computation. In addition, XAI is able to address users' issues on bias or mistake, as it is easier for stakeholders and developers to recognize and correct wrong conclusions. By explaining AI procedures, XAI not only brings about better trust from the user but also facilitates the use of AI assistants in trust-critical applications like career guidance, where users must interpret and act on AI-generated suggestions that may significantly affect their professional trajectory—precisely the context examined in this thesis. [19].

Algorithmic Bias and Perceived Fairness

Users are not only concerned with how accurate AI recommendations are, but also with how fair and unbiased they appear. Studies show that perceived bias in recommendations—even if unintended—can reduce trust and adoption intention [20]. In career contexts, bias may emerge in skill interpretations, role suggestions or labor market data, reinforcing structural inequalities. Addressing algorithmic fairness thus becomes essential not only from an ethical standpoint, but also to foster user trust and perceived legitimacy [21].

Resistance to Automation

The majority of users show psychological resistance to the acceptance of AI, particularly if automation threatens traditional human roles. This result was already captured in Longoni's study about AI acceptance in the early adopting medical industry [22]. In career and educational guidance, individuals feel that AI cannot potentially replace human instincts, emotional intelligence, and personalized mentorship entirely. Research reveals that individuals are likely to accept AI as long as they collaborate with humans and are not completely replaced [4].

Data Security and Privacy Concerns

Artificial intelligence models rely on large volumes of datasets in order to make precise recommendations, thus bringing about issues related to data privacy and security. Users worry about how their personal data is gathered, stored, and processed in AI-driven platforms. This is particularly relevant in the case of career coaching platforms where sensitive data is being processed. Literature indicates that users will be more interactive with AI tools if they are confident that privacy policies and ethical protections are properly in place [23].

With the psychological barriers and the central role of trust in the adoption of artificial intelligence, it is critical to apply theoretical models to describe the processes and logic underlying users' intentions to adopt technology-based career guidance [24]. In the next section, we introduce two popularly accepted models—Technology Acceptance Model and Diffusion of Innovation—to explain the determinants of user adoption and the process by which innovations propagate among various user segments.

2.3 Theoretical Framework for Measuring User Adoption

2.3.1 The Technology Acceptance Model

The Technology Acceptance Model posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) drive individual adoption of new technologies (Davis, 1989). If users see a tool as beneficial (high PU) and simple to operate (high PEOU), they are more likely to develop a positive attitude toward using it. In an AI career-coaching context, PU could be how much the system aids career decisions, while PEOU refers to how effortless it is to interact with.

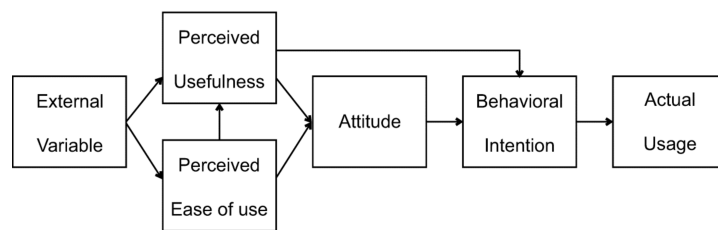


Figure 2.1: Illustration of the Technology Acceptance Model

Over time, TAM has been extended to include factors like trust and privacy. Users need confidence that an AI tool will safeguard their data and provide reliable, unbiased recommendations [25]. Privacy concerns can undermine positive perceptions, even if PU and PEOU are high [26]. Engagement factors, such as whether the coaching interface feels supportive and personalized, can further influence sustained use.

2.3.2 Supplementary Model: Diffusion of Innovation

Rogers' Diffusion of Innovation theory [27] explains how new ideas spread across different adopter categories: innovators, early adopters, early majority, late majority, and laggards. Each group has distinct attitudes and risk profiles. Innovators and early adopters are typically more tolerant of uncertainty, while later groups want proof of benefits.

In the context of AI career coaching, early adopters might be tech-savvy professionals eager to experiment. Their success stories can encourage more hesitant users to try the tool. Eventually, broader segments will adopt once they see social proof and observe tangible value in skill development or job attainment. However, late adopters may remain cautious until AI becomes standard practice in career services.

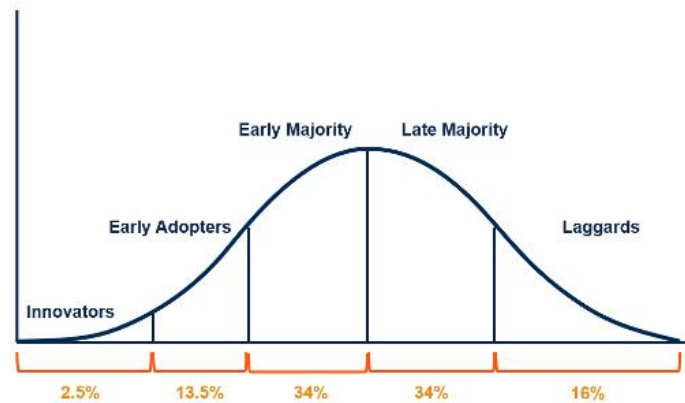


Figure 2.2: Illustration of the Diffusion of Innovation Model

2.3.3 Combining TAM and DOI

Combining TAM and DOI yields a more comprehensive view of adoption. TAM illuminates why a person decides to use the AI coach by examining PU, PEOU, trust, and privacy concerns. DOI places that decision in a social and temporal context, showing how adoption evolves within a community over time [28].

Early adopters often have high PU perceptions and low risk aversion, and they influence the early majority. If PU and PEOU are strong, adoption can spread quickly. If trust is low, diffusion may stall. An integrated TAM-DOI approach thus addresses both individual decision-making (TAM) and broader social dynamics (DOI). As [29] illustrate, unified models that incorporate elements from multiple theories can predict usage more accurately than single-theory approaches.

This thesis adopts such an integrated framework to examine adoption patterns in AI-based career recommendation, highlighting how individual trust, perceived usefulness, and innovation openness interact in a highly personal decision-making environment.

3 Methodology

In this chapter, we describe the methodology for investigating our three core research questions regarding (1) early adopter profiles, (2) acceptance factors, and (3) long-term engagement with AI-driven career coaching. We begin by justifying the survey-based approach, then detail participant selection, data collection procedures, and our rationale for interpreting the outcomes.

3.1 Research Approach

An online survey is well-suited to investigate technology adoption because it can reach a broad population and quantitatively capture users' perceptions and intentions. Furthermore, they allow the generalization of the captured results. Surveys allow to measure key acceptance constructs (e.g. perceived usefulness, ease of use, trust) through standardized scales and statistically analyse their influence on adoption. As a reference model the Technology Acceptance Model, which is widely used for these kind of research projects, was taken [30]. Additionally, a section of open questions was also included into the questionnaire, so that there is a qualitative analysis of the potential user perceptions on the subject, which allows access to new points of view and challenges as a differential aspect to the research [31].

In particular, the constructs on Perceived Usefulness, Ease of Use, and Trust map to Research Question 2, which investigates the key acceptance factors influencing AI career coaching adoption. Meanwhile, items measuring AI Awareness and demographic data help identify likely early adopters (Research Question 1), and engagement-related questions (e.g., willingness to continue using AI) address Research Question 3 by examining long-term participation.

3.2 Data Collection

A standardized online questionnaire, published via Qualtrics, served as the primary research instrument. This method allows for gathering data from a broad sample while remaining user-friendly and freely available for academic use at Católica Lisbon SBE [32]. Staying consistent with the research objectives, the survey was divided into multiple sections—screening, main constructs (TAM variables), open-ended items, and demographics—ensuring a logical flow for participants. The complete questionnaire is reproduced in Appendix A for reference.

3.2.1 Survey Instrument

Below is a two-part table that concisely outlines the key sections and content of the survey. Each section's title is listed in the left column, while the right column provides a brief description of the questions or constructs covered.

Section	Description
Screening	First, respondents were asked if they currently live in a German speaking country. Anyone selecting "No" was exited from the survey to maintain a consistent geographic sample.
Main Survey Sections	<p>Awareness & Familiarity: Items measured prior experience with career guidance (Q2) and level of familiarity with AI tools in general (Q3). Participants were also asked if they had previously consulted AI (e.g., ChatGPT) for career advice (Q4).</p> <p>Career Dissatisfaction: These questions assessed current job satisfaction (Q5) and frequency of considering alternative roles (Q6).</p> <p>Perceived Usefulness & Ease of Use: Aligned with TAM, participants responded to statements on how helpful they believe an AI coach could be for finding new opportunities (Q7–Q8) and how easy they find using such a tool (Q9–Q10). To simplify this section a mock-up of the prototype was included.</p> <p>Trust, Privacy, and Relevance: This block explored participants' trust in unbiased AI matching (Q11), whether they'd trust recommendations more with explanatory details (Q12), and their comfort level regarding data sharing/deletion (Q15–Q16). One open-ended item asked "What makes you trust AI-generated suggestions less than human ones?" (Q14), capturing direct opinions on trust barriers. Participants also rated how likely they would be to act on AI-based job recommendations (Q17).</p>

Table 3.1: Overview of the Survey Sections (Part 1)

Section	Description
Engagement & Long-Term Intentions	These questions gauged whether participants would use an AI tool for career shifts if widely available (Q18), and if they would revisit AI coaching for ongoing career development (Q19). A ranking question prompted participants to prioritize which additional consulting services (e.g., CV adjustment, interview prep, salary negotiation tips) they would find most valuable post-initial AI coaching (Q20).
Open-Ended Reflection	Participants could share broader views on the advantages or challenges of AI-driven tools for exploring new roles (Q21) and leave any further remarks in an optional comment box (Q22).
Demographics	Finally, participants answered questions on age, gender, employment status, field, and education level to allow segmentation and comparative analyses.

Table 3.2: Overview of the Survey Sections (Part 2)

Data was gathered using a non-probability sample—combining convenience and snowball sampling [33]. Although efficient and cost-effective, this approach carries a heightened risk of bias due to non-random selection. As such, the generalizability of the results should be interpreted with caution. The survey link was disseminated via social media (e.g., LinkedIn, Instagram and WhatsApp), with participants encouraged to share it further. Before the final distribution, the survey instrument was pretested with five participants from the target population to ensure clarity, logical flow, and technical functionality. Minor adjustments were made based on their feedback to improve item wording and user experience. Of the total responses collected, incomplete or disqualified submissions were excluded, leaving a final sample size for analysis that met the study’s screening requirements.

3.3 Data Analysis

The data analysis was conducted using Statistical Package for the Social Sciences (SPSS). All collected responses underwent descriptive statistical analysis (e.g., means, standard deviations (SD), frequency distributions) to characterize the sample and gauge overall acceptance levels. For key constructs such as Perceived Usefulness, Ease of Use, and Trust, reliability and inferential tests (e.g., correlations, t-tests, multiple regression) were conducted to assess their relationship with behavioural intention [34]. Based on the TAM, a positive association between Perceived Usefulness and the intention to adopt AI-powered career coaching was theoretically expected and statistically examined.

To ensure methodological rigor, all composite scales and calculated values were systematically tested for internal consistency (reliability), construct validity, and statistical significance. Cronbach's alpha was used to assess scale reliability, while correlation structures and model fits were used to evaluate construct validity and predictive strength within the TAM framework.

Of the initial 161 participants, 14 were excluded from the analysis because they did not reside in a German-speaking country, ensuring geographic consistency in the sample. An additional 16 responses were removed due to incomplete data. The resulting final dataset of 130 fully completed surveys offers a consistent and clean basis for statistical analysis. This completeness across all key variables allows for reliable computation of correlations and regressions, ensuring that all multivariate models are based on uniform response sets without missing values or structural gaps [34].

Qualitative data from the open-ended questions were analysed using thematic analysis, following the six-phase framework by Braun and Clarke (2006) [35]. This inductive approach allowed for the identification of recurring topics, concerns, and motivational patterns. These qualitative insights were used to contextualize and enrich the interpretation of the quantitative findings.

4 Analysis

This chapter presents the empirical results derived from the quantitative survey data and also a qualitative section with the open questions, in which participants could share their thoughts about AI-career consulting. The analysis aims to understand who is most inclined to adopt a cross-industry AI career guidance platform, what factors most strongly influence user acceptance based on the Technology Acceptance Model [36], and which perceived benefits are associated with sustained engagement. To explore these questions, a combination of descriptive statistics, correlation analyses, and multiple regression models is applied.

4.1 Demographics

The sample was predominantly young. Most participants (65.38%) were aged between 25 and 34, with the second-largest group being those aged 18 to 24 (16.92%). Participants aged 35 to 44, 45 to 54, and 55+ made up progressively smaller portions of the sample, each accounting for between 4% and 7%. In terms of gender, the sample was nearly evenly distributed: 50.0% identified as male, 49.23% as female, and 0.77% as non-binary or diverse.

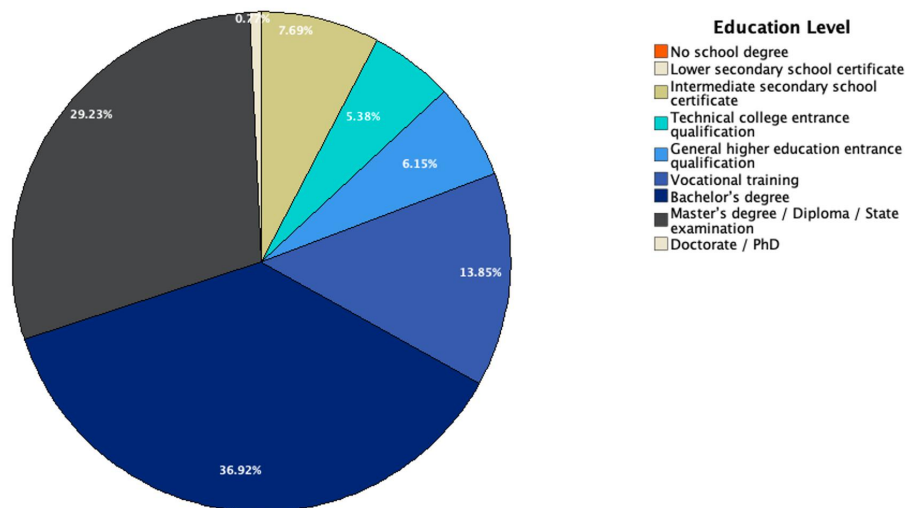


Figure 4.1: Distribution of participants education levels (survey data)

The majority of respondents reported a higher education degree. Specifically, 36.92% held a bachelor's degree and 29.23% had completed a master's degree, diploma, or state examination.

Vocational training accounted for 13.85%, while only 0.77% held a doctoral degree. Lower levels of formal education such as intermediate or secondary school certificates were represented to a lesser extent.

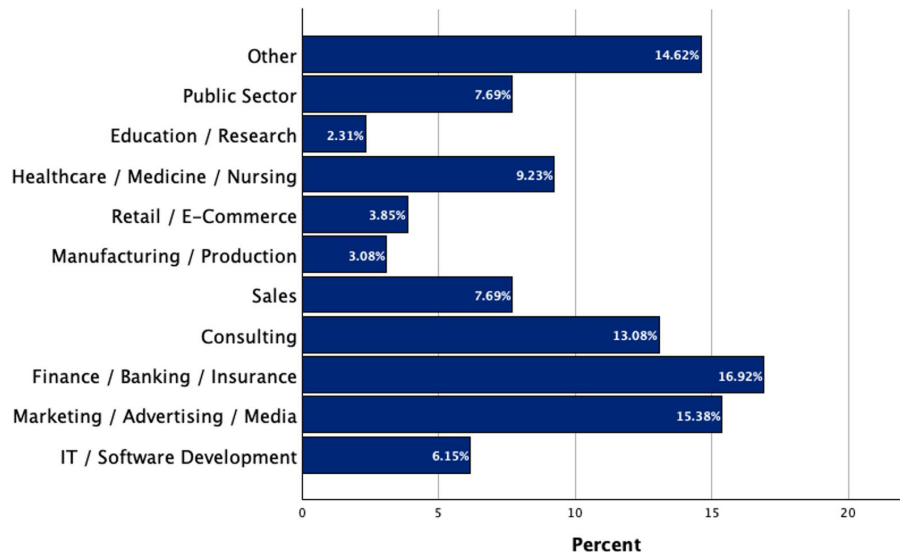


Figure 4.2: Distribution of job profiles (survey data)

Participants came from a wide variety of professional sectors. The most prominent fields included finance, banking, and insurance (16.92%), marketing and media (15.38%), and consulting (13.08%). The category "Other" also made up a significant share at 14.62%, likely encompassing interdisciplinary or niche roles such as construction work, automotive services, and other specialized professions. Healthcare, public sector, and sales followed in moderate proportions. Technical fields like IT (6.15%) and manufacturing (3.08%) were represented to a lesser extent, with education and research accounting for the smallest share (2.31%).

As mentioned in the previous chapter, the focus area for an AI-powered career platform is the German-speaking market, including Germany, Switzerland, and Austria (the DACH region), which are culturally similar. All 130 participants in this study are from the DACH region.

4.2 Descriptives

The descriptive analysis reveals several notable insights into participants' attitudes and prior experiences regarding career guidance and AI tools. A total of 56.9% of participants (n=74) reported having already used ChatGPT or a similar AI model for career-related questions, while 43.1% (n=56) had not. Furthermore, when asked whether they had previously considered a different career path or job profile, a combined 74.6% agreed or strongly agreed with this statement

($n=97$), indicating a high degree of career reflection among the sample. Only 2.3% ($n=3$) stated they had never considered changing paths.

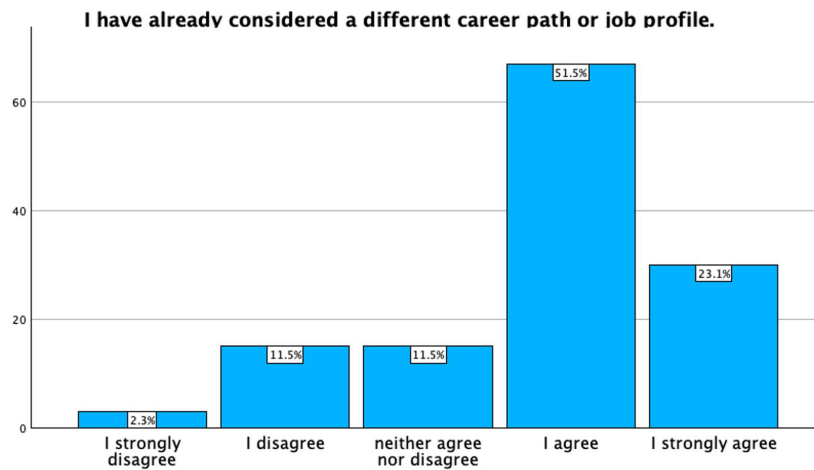


Figure 4.3: Distribution of consideration for different career paths (survey data)

This openness is also visually reflected in the bar chart (see Figure 4.3), where the majority of participants indicated agreement or strong agreement with the statement. The steep rise in frequency at the higher end of the Likert scale suggests that a large proportion of respondents are actively questioning their current professional trajectory. This already indicates a valuable orientation toward possible user segments for an AI-powered career platform—namely individuals who are exploring or reconsidering their professional direction.

The results further show that participants generally expressed a positive attitude towards the core concepts of the proposed career tool. The average agreement to the statement "I can imagine using a career counseling service" was 3.65 (SD = 0.91) on a 5-point scale. A similar value was recorded for familiarity with AI tools ($M = 3.65$, $SD = 0.94$). The mean satisfaction with their current professional situation was slightly lower ($M = 3.62$, $SD = 0.96$), whereas the highest agreement was found for the consideration of a career change ($M = 3.82$, $SD = 0.99$). These results suggest that a substantial share of respondents is not only open to digital career support but also already familiar with AI tools and in a phase of active career orientation.

4.3 Scale Reliability

Although the measurement scales used in this study were based on previously validated instruments, internal consistency was reassessed to ensure reliability within the present sample. As scale reliability can vary depending on sample characteristics and survey context, Cronbach's alpha (α) was calculated for each construct [37]. A reliability coefficient above .60 is generally

considered acceptable, particularly for exploratory research [38]. However, as noted by Streiner [39], values below .50 raise concerns about item coherence, while values above .90 may suggest redundancy.

The Perceived Usefulness scale was based on two items: “An AI career coach would help me find alternative jobs that better match my skills and interests” and “An AI-driven tool could save me time when searching for new career opportunities.” While a statistically significant positive correlation was observed between the two items ($r = .214$, $p = .014$), the Cronbach’s alpha was relatively low at .346, indicating limited internal consistency. Despite this, a composite mean score (PU_Mean) was retained for further analysis, acknowledging the exploratory nature of the study. This decision was further supported by the theoretical coherence of both items within the TAM framework and their conceptual alignment in measuring perceived usefulness.

The Perceived Ease of Use scale, also comprising two items — “It would be easy for me to input my professional experience, personality, and interests into an AI career coach” and “The steps required to receive AI-driven job recommendations would be straightforward for me” — demonstrated an acceptable level of internal consistency ($\alpha = .622$). Given the two-item structure and theoretical alignment, a composite score (PEOU_Mean) was calculated.

The scale measuring Trust in AI was composed of three items: “I believe that an AI system could objectively suggest suitable alternatives without bias,” “Would your trust in an AI recommendation increase if the system explained why it made a specific suggestion?” and “I would trust recommendations from an AI as much as (or more than) those from a human career advisor.” The reliability coefficient ($\alpha = .495$) indicated relatively low internal consistency. Nevertheless, the inter-item correlations were statistically significant and positive (r ranging from .250 to .264, all $p < .01$), suggesting shared variance among the items. Based on this, a mean index (Trust_Mean) was computed and used in the subsequent analyses.

In contrast, the two items intended to capture perceived data privacy concerns — “I feel comfortable sharing personal career history and interest data with an AI tool” and “I would find it reassuring if my data were automatically deleted after, for example, 30 days” — did not meet the reliability threshold. Cronbach’s alpha was negative ($\alpha = -.216$), and the correlation between the two items was weak and statistically insignificant ($r = -.098$, $p = .268$). As a result, no aggregated score was created. The items were retained and analyzed individually.

Lastly, the Adoption Intention scale, composed of two items — “I can imagine applying for a job recommended by an AI” and “I would use an AI tool to explore potential career changes if it were widely available” — achieved a Cronbach’s alpha of .681, supported by a strong inter-item correlation ($r = .516$, $p < .001$). This level of reliability was deemed acceptable, and a composite

mean score (AdoptionIntent_Mean) was calculated for further testing.

Having established the internal consistency and conceptual validity of the key measurement constructs, the following section turns to the first research question: identifying which individuals are most likely to become early adopters of AI-powered career platforms. By examining both demographic and experiential factors, the analysis seeks to uncover patterns in openness and readiness to engage with this emerging form of guidance.

4.4 Early Adopters of AI-Powered Career Platforms

Building on the established reliability of the core constructs, this section explores which individuals are most likely to adopt AI-based career guidance tools. Using the previously constructed Adoption Intention scale, we examine how adoption relates to demographics, AI experience, and openness to career change. The aim is to uncover which user profiles are particularly receptive to such tools, offering insight into potential early adopters.

4.4.1 General Adoption Intention and Demographics

To begin the analysis of early adopters, the overall adoption intention was first examined descriptively. The histogram in Figure 4.4 reveals a positively skewed distribution with a clear tendency toward higher adoption scores.

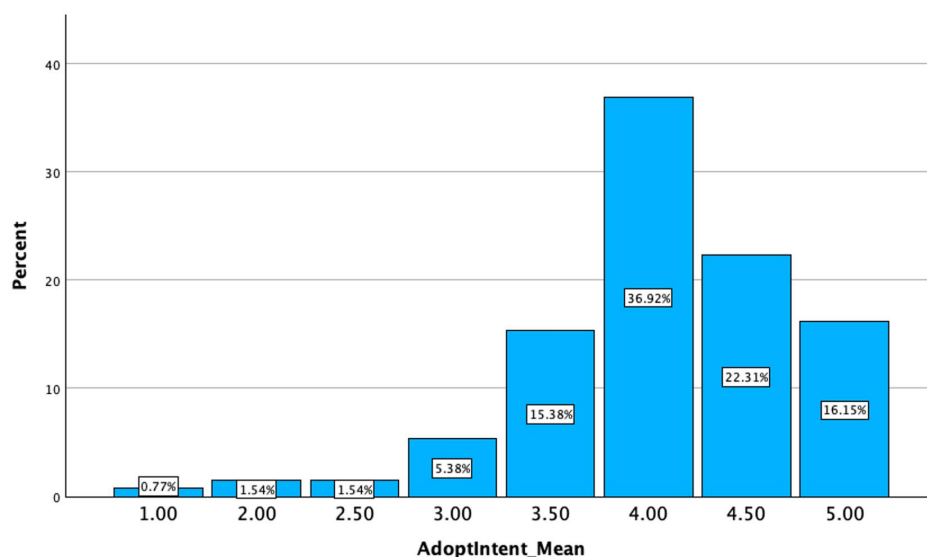


Figure 4.4: Distribution of Adoption Intention (survey data)

The mean adoption intention was 4.07 (SD = 0.69), indicating that, on average, respondents expressed a relatively strong willingness to engage with an AI-powered career guidance plat-

form. Most participants scored between 3.5 and 5, suggesting an overall openness toward such digital tools. This distribution provides a strong foundation for exploring which demographic or behavioural traits are most closely associated with this adoption tendency.

To investigate whether adoption intention is associated with basic demographic characteristics, Pearson correlations were calculated between the `AdoptIntent_Mean` score and participants' age group, current employment status, and highest educational attainment. As a result, none of the examined variables displayed a statistically significant correlation with adoption intention (all $p > .10$). The correlations were weak in magnitude, with age ($r = -.118$, $p = .180$), employment status ($r = -.013$, $p = .881$), and education level ($r = .068$, $p = .442$) showing no meaningful linear association.

These findings suggest that openness to adopting AI-based career coaching is not systematically tied to these general demographic indicators in this sample. One possible explanation lies in the already high baseline of adoption intention across participants, which may have reduced variability and thus limited the potential for detectable linear associations with demographic traits.

An independent samples t-test was conducted to compare adoption intention between genders. The results revealed no significant difference between male and female participants ($t(127) = 1.33$, $p = .185$). The mean difference of .16 was small, and the 95% confidence interval $[-.08, .40]$ included zero, suggesting no systematic variation in adoption intention by gender.

Across nearly all industries, the boxplot in Figure 4.5 illustrates a consistently high level of adoption intention, with median scores clustering toward the upper end of the scale. This widespread positivity suggests a general openness to AI-based career coaching solutions across professional backgrounds.

However, several industries stand out with especially strong adoption levels. Participants in Education / Research, Retail / E-Commerce, and Marketing / Advertising / Media displayed not only high medians but also tightly clustered values, indicating a particularly unified and enthusiastic stance within these groups. This may reflect a greater familiarity with digital tools in these fields or a stronger cultural alignment with innovation and self-guided learning.

At the same time, certain professional groups revealed a broader spread of responses and more frequent outliers. In particular, the Finance / Banking / Insurance and Other categories included individuals with markedly lower adoption scores, deviating substantially from their group's central tendency. These outliers may point to reservations based on data sensitivity, regulatory awareness, or more conservative organizational cultures. The Other category, likely comprising niche or cross-functional roles, also showed greater variability—suggesting a more fragmented

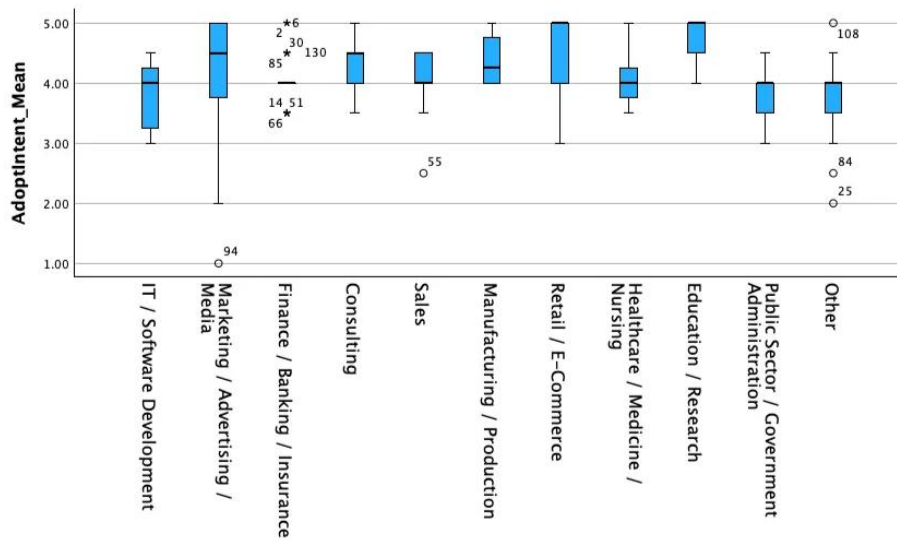


Figure 4.5: Boxplot visualization of adoption intention across professional industries (survey data)

perception of AI-driven career support in less standardized job contexts.

While the boxplot provided a valuable first impression of industry-level differences, the visual variation alone is insufficient to determine whether these differences are statistically meaningful. To formally test whether adoption intention varied across occupational groups, a one-way Analysis of Variance (ANOVA) was conducted. Although the overall model did not reach statistical significance ($F(10, 119) = 1.41, p = .184$), the effect size ($\eta^2 = .106$) points to a moderate practical relevance, indicating that industry affiliation could still meaningfully shape adoption behavior. However, unequal group variances (Levene’s $p = .024$) and imbalanced subgroup sizes may have limited the statistical power of the test, warranting cautious interpretation.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6.478	10	.648	1.409	.184
Within Groups	54.716	119	.460		
Total	61.194	129			

Figure 4.6: ANOVA summary table (survey data)

Overall, while the high average across all industries underscores strong cross-sectoral receptiveness, these nuances highlight that specific occupational environments may shape both enthusiasm and skepticism toward AI-based career guidance.

4.4.2 Adoption Intention and Familiarity with AI

Following the analysis of industry-related differences, the next step was to examine whether previous interaction with AI tools—specifically ChatGPT or similar models—was associated with higher adoption intention. Given that familiarity with technology is a key predictor in acceptance models such as TAM, this comparison provides further insight into the behavioral profiles of potential early adopters.

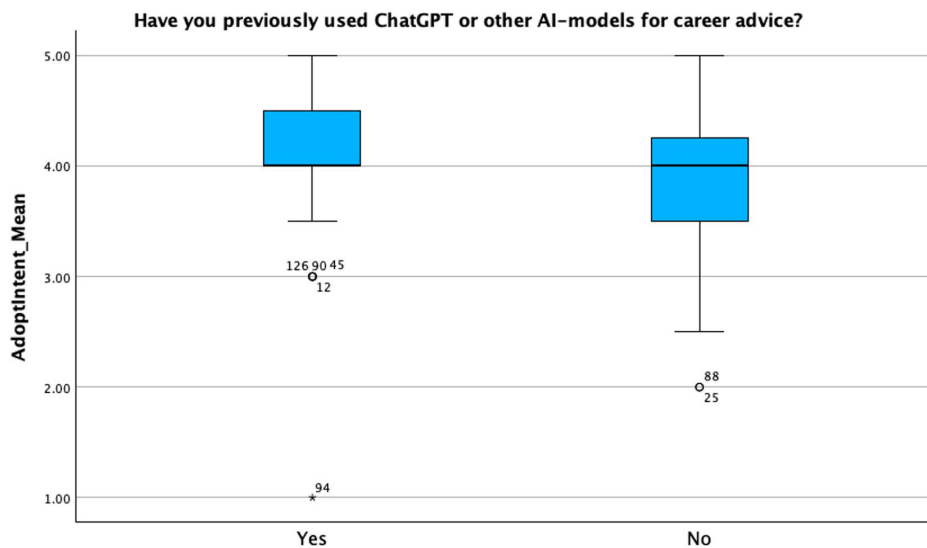


Figure 4.7: Boxplot of adoption intention by prior AI use for career advice (survey data)

A boxplot comparing adoption intention between participants who had previously used ChatGPT for career-related questions and those who had not revealed a clear difference in central tendency, with noticeably higher values among prior users. To test whether this observed difference was statistically significant, an independent samples t-test was conducted. The results confirmed a significant difference between the two groups ($t(115.77) = 2.25, p = .026$), with prior users reporting higher adoption intention on average (mean difference = 0.27). The effect size was medium ($d = 0.40$), suggesting practical relevance.

These findings imply that prior hands-on experience with AI tools may foster greater openness and willingness to engage with AI-powered career guidance platforms. Such results align with the notion that familiarity reduces uncertainty and increases perceived usefulness—especially in technology-mediated decision contexts [25].

4.4.3 Adoption Intention and Psychological Factors

Beyond demographic traits and technical familiarity, psychological factors such as attitudes, self-assessed openness, and past career reflections may offer deeper insight into what drives

individuals toward adopting AI-based career guidance. To further refine the profile of potential early adopters, several experience- and mindset-related variables were examined in relation to adoption intention using correlation analyses and group comparisons. This approach helps to identify underlying motivational patterns that demographic indicators alone cannot fully capture.

		Correlations				
		AdoptIntent_Mean	I can imagine using a career counseling service.	I feel familiar with AI tools (Artificial Intelligence).	I am currently very satisfied with my professional situation.	I have already considered a different career path or job profile.
AdoptIntent_Mean	Pearson Correlation	1	.311**	.288**	-.092	.188*
	Sig. (2-tailed)		<.001	<.001	.300	.033
	N	130	130	130	130	130
I can imagine using a career counseling service.	Pearson Correlation	.311**	1	.134	-.244**	.280**
	Sig. (2-tailed)	<.001		.128	.005	.001
	N	130	130	130	130	130
I feel familiar with AI tools (Artificial Intelligence).	Pearson Correlation	.288**	.134	1	-.037	-.054
	Sig. (2-tailed)	<.001	.128		.673	.542
	N	130	130	130	130	130
I am currently very satisfied with my professional situation.	Pearson Correlation	-.092	-.244**	-.037	1	-.293**
	Sig. (2-tailed)	.300	.005	.673		<.001
	N	130	130	130	130	130
I have already considered a different career path or job profile.	Pearson Correlation	.188*	.280**	-.054	-.293**	1
	Sig. (2-tailed)	.033	.001	.542	<.001	
	N	130	130	130	130	130

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

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

Figure 4.8: Correlation Matrix with Adoption Intention (survey data)

To examine psychological and motivational predictors of adoption intention, Pearson correlation analyses were conducted for several attitudinal and experience-related variables. As shown in Figure 4.8, adoption intention was moderately and significantly associated with both openness to traditional career counseling ($r = .311$, $p < .001$) and perceived familiarity with AI tools ($r = .288$, $p < .001$). These findings suggest that individuals who are generally receptive to external career guidance—and who feel confident in using AI—are more inclined to adopt AI-powered coaching platforms.

Moreover, participants who had previously considered a different career path also showed significantly higher adoption intention ($r = .188$, $p = .033$), indicating that personal career reflection may play a role in shaping openness to innovative forms of guidance.

Surprisingly, satisfaction with one's current professional situation did not correlate significantly with adoption intention ($r = -.092$, $p = .300$). This result challenges the common assumption that dissatisfaction is a primary driver of career-seeking behaviour. Instead, it suggests that openness to AI-based guidance may stem more from a proactive interest in development than from reactive dissatisfaction with one's current status.

To identify which combination of psychological and demographic characteristics best explains adoption intention, a multiple linear regression analysis was conducted. The model included

the following predictors: openness to career counseling, familiarity with AI tools, prior career change consideration, trust in AI (composite score), age, and gender.

The overall model was statistically significant, explaining approximately 35% of the variance in adoption intention ($R^2 = .348$, Adjusted $R^2 = .316$, $F(6,123) = 11.03$, $p < .001$). This indicates a strong explanatory power for behavioral sciences, where R^2 values above .25 are often considered substantial [40]).

Three psychological variables emerged as significant positive predictors: perceived usefulness of career counseling ($\beta = .206$, $p = .009$), familiarity with AI ($\beta = .212$, $p = .008$), and trust in AI systems ($\beta = .421$, $p < .001$). Among them, trust had the strongest standardized coefficient, highlighting it as the most influential driver of adoption intention within the model.

Conversely, demographic variables such as age ($\beta = -.010$, $p = .892$) and gender ($\beta = -.057$, $p = .443$), as well as openness to career change ($\beta = .060$, $p = .445$), did not contribute significantly to the model. These results are consistent with previous findings in this section, confirming that demographic characteristics play a minimal role in shaping adoption willingness in this context.

Collinearity diagnostics confirmed no multicollinearity issues, with Variance Inflation Factor (VIF) values ranging from 1.05 to 1.16 and all tolerance values above .85.

In summary, these results suggest that psychological readiness and prior experiences with AI-driven services—particularly trust and familiarity—are far more indicative of adoption potential than static background traits such as age or gender. This insight supports the notion that effective user targeting and platform design should emphasize trust-building measures and accessible onboarding experiences over demographic segmentation.

4.5 Most Influential User Acceptance Factors

To gain deeper insight into what drives or hinders the adoption of AI-powered career platforms, this section focuses on identifying the most influential user acceptance factors. Guided by TAM, the analysis investigates how core constructs—such as perceived usefulness, perceived ease of use, and trust in AI—relate to adoption intention. Each construct was measured through multiple-item scales and examined for statistical association using Pearson correlations.

In addition, a regression model was employed to determine the relative predictive power of these factors, highlighting which perceptions play the most decisive role in shaping user attitudes. By combining quantitative scale data with qualitative feedback from open-ended survey responses, the analysis aims to capture both measurable patterns and subjective user concerns—providing

a comprehensive understanding of what makes such platforms appealing or problematic in the eyes of potential adopters.

4.5.1 Explaining Adoption: The Role of the TAM Parameters

Initial correlation results provide a clearer picture of the individual strength of each factor before assessing their combined influence. Perceived usefulness demonstrated the strongest statistical association with adoption intention ($r = .616, p < .001$), underscoring its central importance in users' decision-making. This finding aligns with prior TAM research emphasizing usefulness as the primary driver of technology adoption decisions. However, some participants raised doubts about the system's ability to generate truly helpful results. One respondent noted: "The tool might give very similar recommendations to a lot of people due to success rate optimization," pointing to concerns about overly generic suggestions. These qualitative insights illustrate that while perceived usefulness is a strong statistical predictor, users' trust in the individualization of recommendations remains a crucial element in how this usefulness is ultimately judged.

Trust in AI emerged as the second most influential factor ($r = .485, p < .001$), suggesting that participants' belief in the reliability and fairness of AI recommendations substantially shaped their openness to the tool. Perceived ease of use also showed a significant, though comparatively weaker, correlation with adoption ($r = .339, p < .001$), implying that intuitive interfaces and simple interactions matter, but to a lesser extent than perceived effectiveness and trust.

Interestingly, participants' comfort with sharing personal data—an indicator of data privacy concerns—was also significantly associated with adoption intention ($r = .433, p < .001$). This result underscores that while users value functionality and reliability, their willingness to disclose sensitive information is likewise a relevant predictor.

To better understand how the identified acceptance factors jointly influence adoption behavior, a multiple linear regression analysis was conducted. This approach allowed for examining the relative strength of each TAM-based construct while controlling for the influence of others. The scatterplot in Figure 4.6 visually confirms the linear relationship between perceived usefulness and adoption intention, reinforcing the theoretical assumption of its central role.

The overall regression model was statistically significant ($F(4, 125) = 30.41, p < .001$), explaining 49.3% of the variance in adoption intention ($R^2 = .493$). This suggests a robust model fit and highlights the explanatory power of user acceptance factors in this context.

Among the predictors, perceived usefulness emerged as the strongest and most consistent driver of adoption ($\beta = .451, p < .001$), reaffirming its foundational role in TAM-based frameworks. Comfort with sharing personal data also proved to be a significant contributor ($\beta = .222, p =$

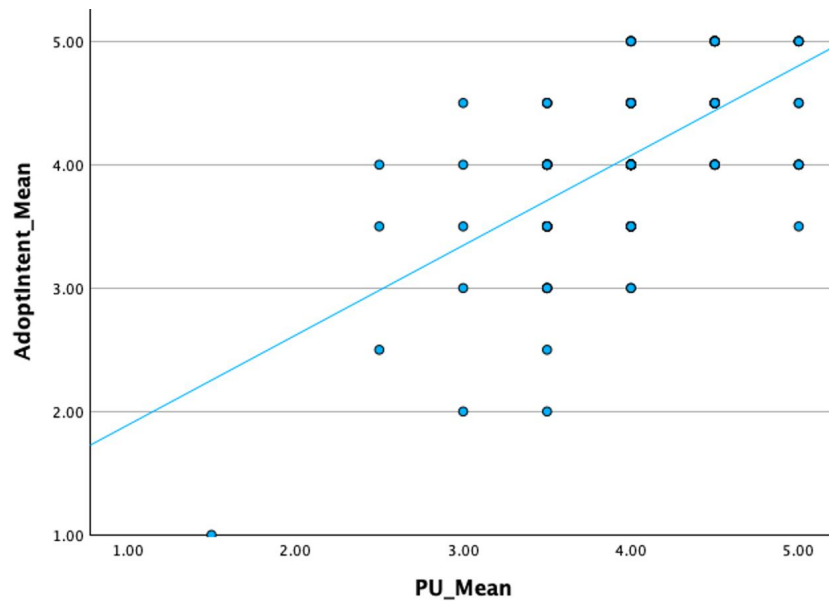


Figure 4.9: Scatterplot of adoption intention by perceived usefulness (survey data)

.002), indicating that privacy trust is a non-negligible consideration in users' decision to engage with AI-powered tools. Trust in AI likewise had a significant, though smaller, effect ($\beta = .179$, $p = .020$), further supporting its inclusion as an important psychological lever. This was echoed in the open responses, where one participant remarked: "The tool can't really comprehend and include soft skills," emphasizing limitations in context understanding and nuance.

In contrast, perceived ease of use did not reach statistical significance in the multivariate model ($\beta = .095$, $p = .173$), suggesting that when usefulness, trust, and privacy are accounted for, usability concerns may play a subordinate role in shaping adoption intention in this sample. However, this does not imply that usability is irrelevant in practice. Especially in digital self-service environments such as AI-powered coaching platforms, perceived ease of use is often a critical determinant of sustained engagement, user satisfaction, and system credibility. Research in the field of information systems consistently shows that even when ease of use is not the primary driver of initial adoption, it becomes essential for continued use and long-term user retention [41].

To ensure the reliability of the regression estimates, multicollinearity was examined using VIF and the Condition Index. All predictors displayed VIF values below 1.5, and the condition indices remained under the critical threshold of 30—indicating no problematic linear dependencies between variables. These diagnostics confirm that the model is stable and the coefficient estimates are robust.

Overall, these findings reinforce the theoretical assumptions of the Technology Acceptance

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.218	.372		.587	.558		
	PU_Mean	.534	.085	.451	6.283	<.001	.786	1.272
	PEOU_Mean	.091	.066	.095	1.372	.173	.841	1.189
	Trust_Mean	.219	.093	.179	2.365	.020	.711	1.407
	I feel comfortable sharing personal career history and interest data with an AI tool.	.158	.049	.222	3.209	.002	.844	1.185

a. Dependent Variable: AdoptIntent_Mean

Figure 4.10: Summary table of the regression analysis (survey data)

Model while highlighting data sharing trust as an influential addition. The results suggest that practical value, psychological confidence in the system, and data handling concerns are key leverage points for increasing adoption of AI-based career coaching platforms.

4.5.2 Impact of Data Protection Features

Beyond general trust in AI systems, concerns about data privacy play a crucial role in shaping user acceptance. To investigate whether privacy-preserving features could enhance trust, a paired-samples t-test was conducted comparing participants' baseline comfort with sharing personal data (Q6_8) and their perceived reassurance if the system were to automatically delete their data after a set period (Q6_9).

The results revealed a significant difference between the two measures. Participants rated the automatic deletion of data ($M = 4.16$, $SD = 0.89$) significantly higher than their general comfort with sharing data ($M = 3.42$, $SD = 0.97$), $t(129) = -6.11$, $p < .001$. The effect size was medium ($d = -0.54$), indicating a meaningful psychological impact.

These findings suggest that concrete data protection mechanisms—such as clearly communicated deletion policies—can substantially increase user trust. While trust in AI already plays a central role in adoption, the presence of specific privacy guarantees appears to deepen this trust and potentially reduce barriers to adoption. This highlights that user acceptance is not only shaped by what the tool can do, but also by how transparently and responsibly it handles user data.

4.5.3 Concerns & Insights from Open-Ended Responses

Building on the regression results, participants were given the opportunity to voice their concerns about AI-powered career coaching through open-text responses. A thematic analysis of 79 comments revealed recurring issues that provide important context for understanding the statistical patterns observed above.

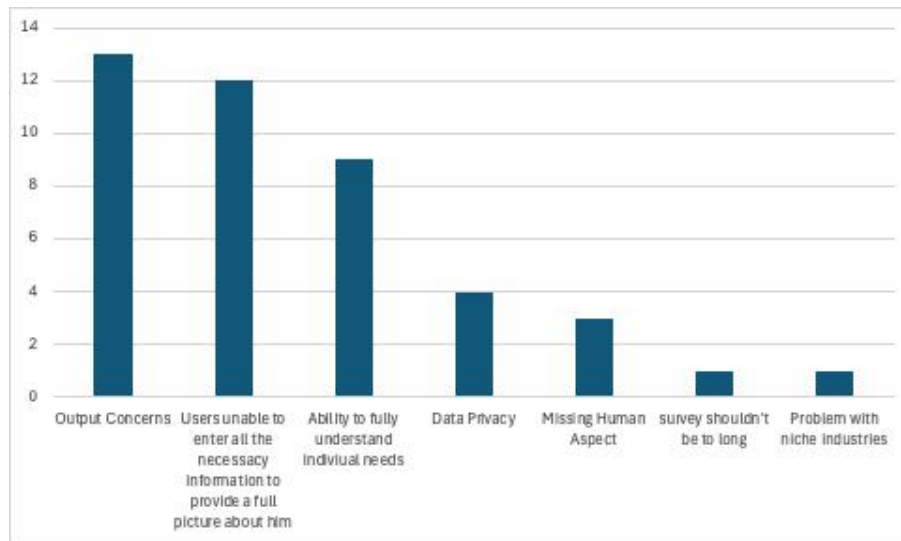


Figure 4.11: Categorization of concerns mentioned in open-ended survey responses (survey data)

The most frequently mentioned theme was output-related concerns ($n = 13$), followed closely by worries about the system's ability to integrate sufficiently detailed input data ($n = 12$) and to understand individual needs ($n = 9$). Respondents questioned whether the tool could deliver personalized advice or whether it would default to generic matches. Specific comments mentioned that “recommendations might be very similar for a lot of people due to success rate optimization” and that the system “can't really comprehend and include soft skills.” These critiques reflect uncertainty about the perceived usefulness and trustworthiness of AI systems. Both of which were shown in the quantitative data to be strong predictors of adoption.

Although data privacy was explicitly mentioned by only four participants, this concern aligns with the moderate yet significant role privacy trust played in the statistical models. Furthermore, as shown earlier, the reassurance provided by data deletion features significantly increased trust—suggesting that while privacy may not be the most salient concern in open commentary, it remains influential on an implicit level.

Additional, less frequently mentioned concerns included the lack of a human element ($n = 3$), survey fatigue ($n = 1$), and doubts about the tool's applicability to niche industries ($n = 1$). While limited in number, these responses point to broader concerns about empathy, adaptability, and inclusivity in AI-driven career tools.

In summary, the open-ended responses provide valuable nuance to the statistical findings of this chapter. While perceived usefulness and trust emerged as key adoption drivers, participants' qualitative feedback highlighted specific vulnerabilities in these areas—particularly around per-

sonalization, soft skill recognition, and output quality. These insights reinforce the need for transparent, flexible, and user-sensitive AI systems if widespread adoption is to be achieved.

Together with the preceding statistical analysis, these findings offer a comprehensive answer to RQ2, identifying not only the most influential user acceptance factors but also the conditions under which users may still hesitate to adopt. This dual perspective forms a crucial foundation for improving future AI-powered career platforms and informs the discussion in the next chapter.

4.6 Long-term Engagement Factors

While the previous sections focused on initial adoption intention and the psychological drivers behind it, long-term user engagement represents the next crucial dimension for the success of AI-based career guidance tools. Adoption alone is not sufficient—sustained usage depends on the platform’s ability to deliver ongoing value tailored to evolving user needs.

To explore this aspect, participants were asked to rank a curated list of potential follow-up features based on their personal preferences. These rankings help identify which functionalities are most likely to encourage recurring use, thereby offering valuable insight for the design of retention-focused platform strategies.

4.6.1 Sustaining Engagement: Ranking Desired Platform Features

Participants evaluated seven features—ranging from practical application support to broader developmental services—on a scale from 1 (most relevant) to 7 (least relevant). The resulting average rank positions reveal a clear preference for concrete, action-oriented support. Specifically, CV optimization ($\bar{O}=2.79$) and cover letter writing ($\bar{O}=3.16$) were rated highest, indicating that users see strong added value in features that directly assist with job application processes.

In contrast, coaching for changing industries ($\bar{O}=5.47$) and skills gap analysis ($\bar{O}=4.69$) received the lowest average rankings. These results suggest that while long-term career development is not entirely dismissed, it holds less immediate relevance for most participants. Instead, the data points to a strong demand for short-term, outcome-driven functionality that can deliver tangible support in navigating the application phase.

4.6.2 Ranking Desires by Engagement Groups

To better understand how long-term user engagement may shape service expectations, participants were divided into two groups based on their stated likelihood of future tool use. This

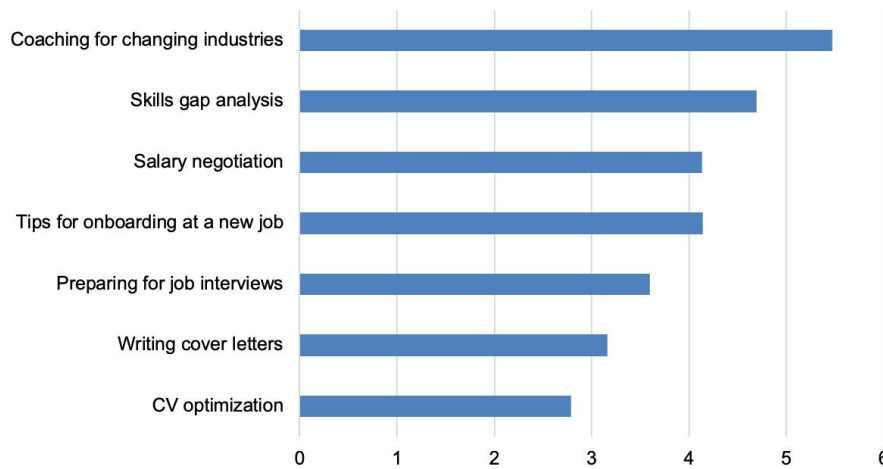


Figure 4.12: Average ranking position for additional features (survey data)

segmentation allows for a more differentiated view of which features appeal to committed versus hesitant users.

Participants who indicated agreement or strong agreement with the statement “I would use this tool again” (response ≥ 4 on a 5-point scale) were assigned to the High Engagement Group ($n=103$). Those who responded neutrally or negatively (<4) formed the Low Engagement Group ($n=27$).

Figure 4.11 displays the mean rank positions of each group for all seven proposed features. Lower values indicate higher perceived usefulness. Across both groups, application-related support clearly dominated. Yet the low-engagement group rated these practical features even more favorably, with CV optimization and cover letter writing both receiving a mean rank of 2.52—lower than in the high-engagement group (2.90 and 3.32, respectively).

Only one feature—preparing for job interviews—was ranked identically by both groups ($M = 3.59$), pointing to its universal appeal regardless of user retention intent.

On the other hand, more future-oriented or developmental services, such as skills gap analysis and coaching for changing industries, consistently ranked lowest. This difference was especially pronounced among low-engagement users. For instance, coaching received a mean rank of 6.11 in this group—nearly a full point higher (i.e., lower preference) than in the high-engagement group (5.29). This disparity suggests that participants who are less inclined to return to the tool also show reduced openness toward transformative or long-term guidance services.

To statistically assess whether these differences in preferences are meaningful, Mann–Whitney U tests were conducted for each feature. This non-parametric test is particularly suited for ordi-

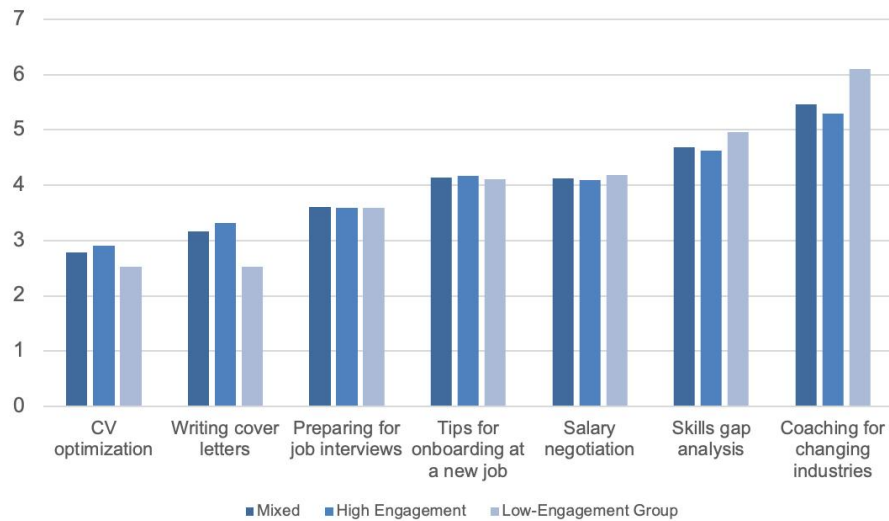


Figure 4.13: Average ranking position by engagement groups (survey data)

nal data such as rankings and allows for group comparisons without assuming a normal distribution.

The results confirmed a significant difference for cover letter writing ($U = 1067.5$, $p = .044$), reinforcing the idea that less engaged users value concrete, low-effort services. By contrast, no significant difference was found for CV optimization ($p = .446$), suggesting that this feature enjoys universal popularity regardless of future usage intent.

Looking further down the ranking, coaching for changing industries showed the most divergence between groups, with low-engagement users ranking it considerably lower (mean rank = 78.06) than high-engagement users (62.21). This difference was also statistically significant ($U = 1051.5$, $p = .040$), indicating that more engaged participants may be more open to future-oriented or transformative guidance services.

Furthermore, features such as preparing for job interviews, onboarding support, salary negotiation, and skills gap analysis showed no significant differences between groups (all $p > .3$), suggesting that these offerings appeal more consistently across engagement levels.

Taken together, the analytical results offer a detailed picture of how different user segments perceive and respond to AI-powered career guidance. With these patterns in mind, the next chapter moves beyond statistical findings to examine their broader meaning, theoretical alignment, and practical relevance.

5 Discussion & Conclusion

After the survey results have been evaluated across user segments, adoption drivers, and engagement patterns, the following chapter turns to a broader interpretation of these findings. The aim is to contextualize the results within the theoretical framework, assess their implications for research and practice, and reflect on how they contribute to our understanding of AI-powered career guidance. In doing so, this section also addresses the study’s limitations and outlines potential directions for future investigations.

5.1 Main Findings

The empirical investigation centered around understanding which user profiles are most likely to adopt AI-powered career guidance tools, what acceptance factors influence their decisions, and which platform features are most valued in the context of long-term engagement.

Starting with RQ1, the goal was to identify potential early adopters of AI-driven career platforms. The results indicate that most general demographic variables—such as age, gender, education level, and employment status do not significantly predict adoption intention. These findings contrast with earlier studies suggesting that older individuals or those with lower educational attainment may be more hesitant toward new technologies [29]. However, they align with more recent research emphasizing psychological and experiential factors over static user traits when it comes to innovation adoption [17].

A different picture emerged when analysing users’ professional background. While adoption intention was broadly high across all industries, participants from Education/Research, Retail/E-Commerce, and Marketing/Media demonstrated the highest levels of adoption intention, with tightly clustered responses near the upper end of the scale. These industries arguably share characteristics such as digital tool familiarity, a culture of innovation, and exposure to user-centric or data-driven work environments, which may make users more receptive to AI-powered platforms. In contrast, participants from more traditional or regulated sectors such as Finance or undefined “Other” categories showed more dispersed values and included more low-scoring outliers. Potentially reflecting reservations about privacy, trust, or system applicability.

Notably, participants who had previously used ChatGPT or similar tools for career-related questions reported significantly higher adoption intentions. This finding suggests that hands-on ex-

perience with AI meaningfully fosters openness, likely by lowering uncertainty and increasing perceived usefulness. Similarly, familiarity with AI tools in general and openness to career counseling were positively correlated with adoption. This pattern aligns with Rogers' Diffusion of Innovation theory, in which early adopters are characterized not by age or background, but by their willingness to engage with new technologies and their comfort with uncertainty. In sum, early adoption seems to depend less on who users are demographically, and more on what they have experienced and how open they are to change and experimentation.

The survey's findings provide a clear answer to RQ2 by highlighting which perceptions most strongly influence the adoption of AI-powered career coaching tools. As predicted by the Technology Acceptance Model, perceived usefulness stood out as the most important driver [36]. When users believe the tool can deliver meaningful and relevant career guidance, their willingness to adopt increases significantly. However, open-ended responses revealed that doubts remain about the tool's ability to generate truly individualized and helpful results. Concerns about generic recommendations or a lack of soft skill consideration show that usefulness is judged not just by functionality but also by perceived personal relevance.

Trust in the system also played a key role. Users were more inclined to embrace AI guidance when they felt confident that recommendations were fair, transparent, and logically sound. This highlights the importance of explainable AI principles in interface and recommendation design. When users understand why a particular job is suggested, they are more likely to perceive the system as credible and aligned with their interests. An effect echoed across both quantitative and qualitative responses.

While perceived ease of use did not reach statistical significance in the final model, this does not negate its role in shaping real-world user behaviour. In practical terms, ease of use remains essential for ensuring continued engagement, particularly among less tech-savvy users and during early onboarding. Compared to the impact of trust, privacy, and perceived usefulness, ease of use appeared less decisive in initial adoption decisions. It can be assumed that once users are convinced of a tool's effectiveness and integrity, the simplicity of the interface becomes a secondary consideration.

Qualitative feedback reinforced these insights. Many participants voiced scepticism about personalization and the depth of insight the system could offer, especially for complex career paths or emotional nuances. These concerns support the importance of thoughtful design that respects both data protection and the individual career context. In addition, several participants expressed worries that users might enter incorrect or incomplete information, potentially leading to misleading outcomes. To address this, the design must guide users in providing accurate and relevant input by using clear instructions and well-structured questions to prevent ambiguity or

misinterpretation.

Having explored the factors that drive initial adoption, the final part of the analysis examined what motivates users to continue engaging with an AI-powered career guidance platform. Participants prioritized features with immediate operational value over abstract or strategic tools. Across all respondents, CV optimization and cover letter writing consistently received the highest rankings. These results indicate that users primarily seek operational support that delivers immediate value, rather than long-term developmental features.

When comparing high- and low-engagement groups, both prioritized application-related services, although the preference was more pronounced among participants with lower engagement. In contrast, participants with higher engagement showed a greater openness to more advanced features such as coaching for changing industries. However, these offerings were generally ranked lower and revealed significant differences only toward the end of the preference list.

While there were statistically significant differences for a few features, the overall pattern points to strong shared priorities across user segments. This suggests that the sustained success of such platforms may depend on initially focusing on universally valued services, then gradually expanding toward more developmental support as users build trust and familiarity. This supports a phased feature rollout strategy. Starting with hands-on tools that deliver immediate value and introducing more advanced coaching elements as user confidence and engagement increase.

5.2 Academic Implications

The conclusions of this study on the adoption and long-term engagement of AI-powered career coaching carry significant implications for both foundational technology-acceptance and innovation-diffusion theories, as well as for the strategic and operational practices of platform providers.

Firstly, the findings both confirm and extend the TAM by demonstrating that trust in data-privacy mechanisms operates alongside perceived usefulness and perceived ease of use to shape adoption intention. Whereas classical TAM research positions PU and PEOU as the primary antecedents of behavioural intention [36]. The results reveal that users' comfort with explicit data-deletion guarantees significantly bolsters their confidence in AI-powered coaching. In practical terms, participants who were assured that their personal data would be purged after predetermined intervals reported higher PEOU and PU scores and, in turn, stronger adoption intentions. This underscores the need to integrate privacy-trust constructs into future TAM-based investigations [29].

Secondly, these insights align with Rogers’s DOI framework by highlighting the role of early adopters as catalysts for broader diffusion (Rogers, 1962). In our sample, individuals with prior AI experience—and elevated trust in transparency measures—comprised the earliest cohort willing to engage with AI career coaches despite residual concerns about personalization and soft-skill recognition. Their readiness suggests that, once equipped with robust privacy assurances and demonstrable value, this segment can serve as opinion leaders whose positive testimonials accelerate adoption among the early majority. Thus, effectively addressing privacy and trust barriers is pivotal not only for initial uptake but also for enabling the classic S-curve diffusion trajectory.

Building on the idea of AI as a boundary agent, it is also crucial to explore how Explainable AI can deepen established coaching theories. In the literature review [19], Explainable AI emerged as a critical trust enhancer, while traditional coaching frameworks such as Goal-Setting Theory and the Working Alliance Model highlight transparency and the strength of the coach–client relationship as essential to effective learning and lasting engagement [11]. Integrating XAI components into these models could therefore yield valuable theoretical insights. By revealing the reasoning behind algorithmic suggestions, explainable algorithms stand to bolster the AI coach’s credibility, reinforce the coach–client alliance and ultimately improve both learning outcomes and sustained user engagement. Future research should systematically expand coaching theories to include XAI features, examining how transparency mechanisms shape the collaborative process between user and AI and transform the dynamics of technology-mediated career development.

5.3 Managerial Implications

A foundational strategy for accelerating platform uptake is to enlist experienced AI users as pilot participants and champions. AI-tool-providers should focus especially on professionals in sectors with high AI and technology-tool usage, such as marketing, research and e-commerce, since our analysis showed they exhibit the strongest early-adopter intent and carry substantial credibility within their networks. By harnessing their enthusiasm and trust, these advocates can initiate powerful word-of-mouth diffusion, helping transition the service from niche innovators to the broader early-majority segment and accelerating its overall adoption trajectory.

Additionally, the analysis shows that users of AI-driven career platforms judge them first and foremost by the tangible value they deliver, defining usefulness as the single most important criterion for continued engagement and word-of-mouth recommendation. To convert newcomers into committed early adopters, onboarding flows must go beyond generic demos and instead showcase concrete examples of success, such as brief case studies or interactive snapshots that

demonstrate how the platform has helped real users land interviews, refine their CVs or pivot into new roles. By guiding new registrants through a mini-journey—uploading a résumé to receive an immediate, personalized improvement suggestion, then seeing how similar users achieved measurable career gains—platforms can create that “aha” moment within minutes of signup. Crucially, this isn’t about simply producing any output, but about delivering genuinely customized advice that resonates with each individual’s background and goals. In doing so, AI-tool providers reinforce perceived usefulness, reduce uncertainty and accelerate uptake among the early-adopter segment.

Building on the emphasis of immediate value, it is equally important to address privacy concerns directly, especially in markets such as Germany where data protection ranks among the top decision factors for adopting AI tools. Users must see that their sensitive career and personal information will be handled with the utmost care. One effective measure is to offer a clear option for automatic data deletion, for example guaranteeing that all uploaded documents and interaction logs are erased after a configurable period such as 30 days.

In addition, platforms should integrate explainable AI components that reveal the reasoning behind each recommendation, making transparent why a particular skill suggestion or industry match was offered. By prominently highlighting both the automatic deletion feature and the rationale disclosures during the onboarding sequence, platforms not only demonstrate compliance with stringent privacy expectations but also directly bolster user trust and credibility. As privacy worries diminish and users understand how and why decisions are made, prospective users feel more comfortable engaging with the tool, leading to higher trial rates and ultimately stronger long-term commitment.

The analysis further reveals that, across all user segments, hands-on features clearly outshine high-level advisory services. In the case of AI-powered career platforms, tools like CV optimization and cover-letter writing consistently earned the top rankings, while more strategic or visionary offerings tended to fall toward the bottom of the list. This pattern underscores a simple but powerful insight: when shaping the product roadmap, AI-tool providers must work hand in hand with their user community to identify and build the features that deliver the most immediate and tangible value. By co-creating those high-impact tools that drive both initial adoption and sustained engagement, platforms ensure they meet real user needs, reinforce trust through responsiveness, and secure a competitive edge.

5.4 Limitations

Self-reported data from an online survey are inherently subject to respondent inaccuracies and misreporting [42]. Although the survey targeted professionals across multiple industries, most of participants were based in Germany, with the remainder drawn primarily from neighbouring European countries exhibiting similar cultural and regulatory environments. This geographic concentration may bias the results and constrain their applicability to markets outside of Western Europe.

The sample also displayed limited demographic diversity, particularly in terms of age and educational background. Nearly two-thirds of participants (65.4 percent) were between 25 and 34 years old, while only 4 to 7 percent fell into each older age bracket. In addition, over 66 percent held at least a bachelor's degree, including 36.9 percent with a bachelor's and 29.2 percent with a master's or equivalent. This concentration of young, highly educated professionals may restrict our ability to assess how broader age groups and education levels affect acceptance of AI-powered career coaching. Such homogeneity is common in studies relying on convenience samples from Western populations, which are known to exhibit psychologically distinct response patterns [43].

A further limitation arises from acquiescence bias in the use of Likert scales, where respondents may disproportionately agree with positively framed statements [44]. In this study, such a tendency could have inflated measures of perceived usefulness, ease of use, and trust in AI coaching. Although the analysis employed robust quantitative methods—including t-tests, correlation analyses, and multiple regressions—to examine relationships among key constructs, the reliance on self-reported attitudinal data leaves room for subjective response patterns. Without additional objective usage metrics or in-depth qualitative validation, the true extent of positive dispositions toward the platform may be overestimated.

An additional constraint stems from the internal consistency of certain composite scales. The low internal consistency of some scales, such as Perceived Usefulness ($\alpha = .346$), may limit the validity of these constructs. One likely reason for this is the low item count, as both PU and PEOU were measured using only two items, which generally increases the risk of underestimating true reliability. These lower coefficients suggest that the items within each composite may not fully capture a unified construct, potentially weakening the validity of subsequent analyses that rely on these aggregated measures. As a result, findings related to these constructs should be interpreted with caution, and future studies might consider refining item phrasing or expanding scale length to enhance measurement robustness [39].

5.5 Future Research

Building on the foundational insights of this study, several directions for future research present valuable opportunities to deepen and expand the current understanding of user acceptance and engagement with AI-powered career platforms. While this thesis offers a first empirical step in identifying psychological and functional adoption drivers, it captures only a snapshot in time. Future research could apply a longitudinal design to observe how user perceptions evolve after repeated platform interaction, particularly in relation to trust, perceived usefulness, and long-term satisfaction. This would allow for a more dynamic understanding of how engagement develops and under which conditions it stabilizes or declines. In parallel, future research should also address the ethical design challenges associated with AI-based career guidance. As such tools become more embedded in personal decision-making, issues of fairness, transparency, and user autonomy demand greater scholarly attention.

Moreover, the sample in this study was predominantly composed of young, highly educated individuals based in German speaking countries. While appropriate for identifying early adopter patterns, the generalizability of these findings is limited. Future studies could explore more heterogeneous and international samples to examine how cultural background, regulatory environments, or digital literacy shape acceptance patterns in different markets.

Another promising direction lies in strengthening the methodological foundation by incorporating behavioral usage data alongside self-reported attitudes. Metrics such as feature-click frequency, time spent on task, or actual return rates to the platform could validate or challenge assumptions drawn from survey responses, reducing potential biases caused by social desirability or acquiescence effects.

Lastly, the role of explainable AI also deserves more focused attention. While this study identified its relevance for trust-building, future research could experimentally test how different levels of algorithmic transparency affect user satisfaction, confidence in recommendations, and willingness to act on the tool's advice. A promising approach could be to design a between-subjects experiment in which participants interact with either a fully transparent AI system that provides rationale for its suggestions, or a black-box model offering only final outputs. Comparing these conditions would offer deeper insights into how explainability mechanisms influence perceived credibility and user trust.

5.6 Conclusion

Artificial intelligence continues to reshape the way individuals approach career development, yet its role in personalized coaching remains relatively underexplored. This study set out to examine which factors drive the adoption and long-term engagement of AI-powered career guidance platforms, focusing on a context where traditional coaching methods are often costly, time-consuming, and poorly tailored to individual needs. Through a combination of theoretical grounding in the Technology Acceptance Model and the Diffusion of Innovation framework, and empirical insights from a user-focused survey, the study uncovers a new layer of understanding in how users interact with AI in highly personal, decision-critical domains.

The findings highlight that perceived usefulness, trust in data privacy, and transparency of recommendations are pivotal for adoption, especially when paired with operationally valuable features such as CV optimization or cover-letter support. While traditional demographic markers showed limited explanatory power, psychological readiness, familiarity with AI tools, and a proactive career mindset emerged as stronger predictors of acceptance. In doing so, this research shifts the conversation from general AI scepticism toward a more nuanced view of how trust and value perception shape user behaviour in private, goal-driven contexts.

Importantly, the study also identifies tangible design and communication strategies for AI-tool providers that aim to foster sustained engagement. From data deletion guarantees to the integration of explainable AI, the results provide actionable implications that bridge theory and practice. They demonstrate how early trust-building and immediate value delivery are key to reaching and retaining critical early-adopter segments.

In light of the limited prior research on AI acceptance in personal domains, this thesis offers a foundational yet forward-looking contribution. It not only provides first empirical insights into a newly emerging digital product category, but also lays the groundwork for future interdisciplinary exploration across technology, psychology, and user experience.

Ultimately, the future of AI in career guidance will not be determined by technology itself, but by the intentions, values, and choices that shape how it is built and used. As Shoshana Zuboff aptly noted: “The key question is not technology, but how humans choose to use it.”

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A Outline of survey questions

Q No.	Question	Question Type	Answer Format
1	Do you live in a German-speaking country?	Screening (Single choice)	Yes / No
2	Have you ever used ChatGPT or a similar AI tool for career-related questions?	Single choice	Yes / No
3	I can imagine using a career counseling service.	Likert (5-point)	Strongly disagree to strongly agree
4	I feel familiar with AI tools (Artificial Intelligence).	Likert (5-point)	Strongly disagree to strongly agree
5	I am currently very satisfied with my professional situation.	Likert (5-point)	Strongly disagree to strongly agree
6	I have already considered a different career path or job profile.	Likert (5-point)	Strongly disagree to strongly agree
7	An AI career coach would help me find alternative jobs that better match my skills and interests.	Likert (5-point)	Strongly disagree to strongly agree
8	An AI-driven tool could save me time when searching for new career opportunities.	Likert (5-point)	Strongly disagree to strongly agree
9	It would be easy for me to input my professional experience, personality, and interests into an AI career coach.	Likert (5-point)	Strongly disagree to strongly agree
10	The steps required to receive AI-driven job recommendations would be straightforward for me.	Likert (5-point)	Strongly disagree to strongly agree
11	I believe that an AI system could objectively suggest suitable alternatives without bias.	Likert (5-point)	Strongly disagree to strongly agree
12	Would your trust in an AI recommendation increase if the system explained why it made a specific suggestion?	Likert (5-point)	Strongly disagree to strongly agree
13	I would trust recommendations from an AI as much as (or more than) those from a human career advisor.	Likert (5-point)	Strongly disagree to strongly agree

Table A.1: Overview of all survey questions, types, and formats (Part 1)

Appendix A: Outline of survey questions

Q No.	Question	Question Type	Answer Format
14	I feel comfortable sharing personal career history and interest data with an AI tool.	Likert (5-point)	Strongly disagree to strongly agree
15	I would find it reassuring if my data were automatically deleted after, for example, 30 days.	Likert (5-point)	Strongly disagree to strongly agree
16	I can imagine applying for a job recommended by an AI.	Likert (5-point)	Strongly disagree to strongly agree
17	I would use an AI tool to explore potential career changes if it were widely available.	Likert (5-point)	Strongly disagree to strongly agree
18	If I found the suggestions of an AI career coach helpful, I would use it regularly for my professional development.	Likert (5-point)	Strongly disagree to strongly agree
19	Which type of follow-up service would you be most likely to use?	Ranking	CV optimization, cover letter, job interviews, onboarding, salary negotiation, skill gaps, industry change
20	What do you see as the biggest advantages or disadvantages of using an AI tool to discover career alternatives?	Open-ended	Free text
21	Do you have any additional comments you would like to share?	Open-ended	Free text
22	What is your age group?	Demographic	18–24, 25–34, 35–44, 45–54, 55+
23	What is your gender?	Demographic	Male, Female, Diverse, Prefer not to say
24	What is your current employment status?	Demographic	Full-time, Part-time, Student, Unemployed, Other
25	Which job profile best describes you?	Demographic	IT, Marketing, Finance, Consulting, Sales, Healthcare, Education, Public sector, Other
26	What is your highest educational qualification?	Demographic	From “No diploma” to “Doctorate”

Table A.2: Overview of all survey questions, types, and formats (Part 2)

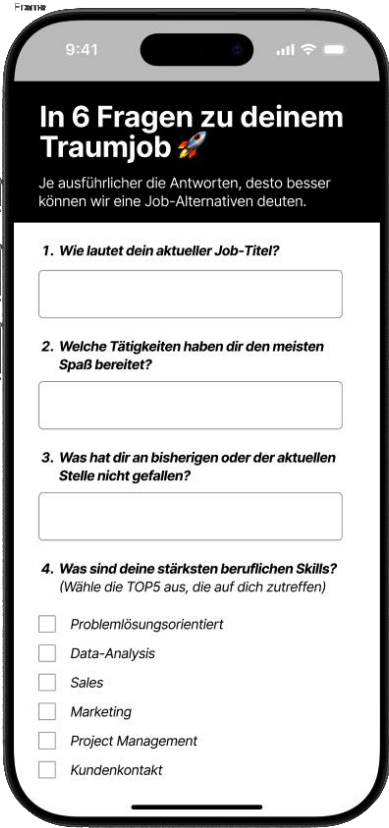


Figure A.1: Illustration of a possible graphical user interface for data collection

B Participants & Demographics

Do you live in a German-speaking country?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	138	90.8	90.8	90.8
	No	14	9.2	9.2	100.0
Total		152	100.0	100.0	

		Frequency	Percent	Valid Percent	Cumulative Percent	
Valid	IT / Software Development	8	6.2	6.2	6.2	
	Marketing / Advertising / Media	20	15.4	15.4	21.5	
	Finance / Banking / Insurance	22	16.9	16.9	38.5	
	Consulting	17	13.1	13.1	51.5	
	Sales	10	7.7	7.7	59.2	
	Manufacturing / Production	4	3.1	3.1	62.3	
	Retail / E-Commerce	5	3.8	3.8	66.2	
	Healthcare / Medicine / Nursing	12	9.2	9.2	75.4	
	Education / Research	3	2.3	2.3	77.7	
	Public Sector / Government Administration	10	7.7	7.7	85.4	
	Other	19	14.6	14.6	100.0	
	Total		130	100.0	100.0	

Have you previously used ChatGPT or similar AI-models for career related questions?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	74	56.9	56.9	56.9
	No	56	43.1	43.1	100.0
Total		130	100.0	100.0	

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
I can imagine using a career counseling service.	130	1	5	3.65	.905
I feel familiar with AI tools (Artificial Intelligence).	130	1	5	3.65	.939
I am currently very satisfied with my professional situation.	130	1	5	3.62	.959
I have already considered a different career path or job profile.	130	1	5	3.82	.994
Valid N (listwise)	130				

To what extent do you agree with the following statement about your career situation? – I have already considered a different career path or job profile.

		Frequency	Percent
Valid	Stimme überhaupt nicht zu	3	2.3
	Stimme nicht zu	15	11.5
	Stimme weder zu noch lehne ich ab	15	11.5
	Stimme zu	67	51.5
	Stimme voll zu	30	23.1
Total		130	100.0

C Scale Assessment

Scale: Perceived Usefulness: Q6_1&2

Case Processing Summary

		N	%
Cases	Valid	130	100.0
	Excluded ^a	0	.0
	Total	130	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.346	2

Correlations

	An AI career coach would help me find alternative jobs that better match my skills and interests.	An AI-driven tool could save me time when searching for new career opportunities.
An AI career coach would help me find alternative jobs that better match my skills and interests.	Pearson Correlation	1
	Sig. (2-tailed)	.214 [*]
	N	130
An AI-driven tool could save me time when searching for new career opportunities.	Pearson Correlation	.214 [*]
	Sig. (2-tailed)	.014
	N	130

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

Scale: PEOU

Case Processing Summary

		N	%
Cases	Valid	130	100.0
	Excluded ^a	0	.0
	Total	130	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.622	2

Scale: Trust in AI mit 3 Items

Case Processing Summary

		N	%
Cases	Valid	130	100.0
	Excluded ^a	0	.0
	Total	130	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.495	3

Correlations

	I believe that an AI system could objectively suggest suitable alternatives without bias.	Would your trust in an AI recommendation increase if the system explained why it made a specific suggestion?	I would trust recommendations from an AI as much as (or more than) those from a human career advisor.
I believe that an AI system could objectively suggest suitable alternatives without bias.	Pearson Correlation	1	.250 ^{**}
	Sig. (2-tailed)		.004
	N	130	130
Would your trust in an AI recommendation increase if the system explained why it made a specific suggestion?	Pearson Correlation	.250 ^{**}	1
	Sig. (2-tailed)	.004	.002
	N	130	130
I would trust recommendations from an AI as much as (or more than) those from a human career advisor.	Pearson Correlation	.264 ^{**}	.264 ^{**}
	Sig. (2-tailed)	.002	.002
	N	130	130

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

Appendix C: Scale Assessment

Reliability: Data Privacy (Q6_8 & 9)

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	130	100.0
	Excluded ^a	0	.0
	Total	130	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha ^a	N of Items
.216	2

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Correlations

	I feel comfortable sharing personal career history and interest data with an AI tool.	I would find it reassuring if my data were automatically deleted after, for example, 30 days.
I feel comfortable sharing personal career history and interest data with an AI tool.	Pearson Correlation Sig. (2-tailed) N	1 .268 130
I would find it reassuring if my data were automatically deleted after, for example, 30 days.	Pearson Correlation Sig. (2-tailed) N	-.098 .268 130

Scale: Adoption Intention

Case Processing Summary

		N	%
Cases	Valid	130	100.0
	Excluded ^a	0	.0
	Total	130	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.681	2

Correlations

	I can imagine applying for a job recommended by an AI.	I would use an AI tool to explore potential career changes if it were widely available.
I can imagine applying for a job recommended by an AI.	Pearson Correlation Sig. (2-tailed) N	1 .516** 130
I would use an AI tool to explore potential career changes if it were widely available.	Pearson Correlation Sig. (2-tailed) N	.516** <.001 130

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

D Research question 1

Descriptives: Adoption Intention

Descriptive Statistics							
	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
AdoptIntent_Mean	130	1.00	5.00	4.0654	.68875	.474	-1.124
Valid N (listwise)	130						.212

Correlations

		AdoptIntent_Mean	Which age group do you belong to?	What is your current employment status?	Education Level
AdoptIntent_Mean	Pearson Correlation	1	-.118	-.013	.068
	Sig. (2-tailed)		.180	.881	.442
	N	130	130	130	130
Which age group do you belong to?	Pearson Correlation	-.118	1	-.105	-.078
	Sig. (2-tailed)	.180		.233	.381
	N	130	130	130	130
What is your current employment status?	Pearson Correlation	-.013	-.105	1	.050
	Sig. (2-tailed)	.881	.233		.575
	N	130	130	130	130
Education Level	Pearson Correlation	.068	-.078	.050	1
	Sig. (2-tailed)	.442	.381	.575	
	N	130	130	130	130

AdoptIntent_Mean

	Frequency	Percent	Cumulative Percent
Valid 1.00	1	.8	.8
2.00	2	1.5	2.3
2.50	2	1.5	3.8
3.00	7	5.4	9.2
3.50	20	15.4	24.6
4.00	48	36.9	61.5
4.50	29	22.3	83.8
5.00	21	16.2	100.0
Total	130	100.0	

Correlations: AdoptIntent & AI-Familiarity

		AdoptIntent_Mean	I feel familiar with AI tools (Artificial Intelligence).
AdoptIntent_Mean	Pearson Correlation	1	.288**
	Sig. (2-tailed)		<.001
	N	130	130
I feel familiar with AI tools (Artificial Intelligence).	Pearson Correlation	.288**	1
	Sig. (2-tailed)	<.001	
	N	130	130

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

T-Test

Group Statistics

	What is your gender?	N	Mean	Std. Deviation	Std. Error Mean
AdoptIntent_Mean	Male	65	4.1462	.60417	.07494
	Female	64	3.9844	.76619	.09577

Independent Samples Test

		Levene's Test for Equality of Variances				t-test for Equality of Means					
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
AdoptIntent_Mean	Equal variances assumed	.102	.750	1.333	127	.092	.185	-.16178	.12139	-.07842	-.40198
	Equal variances not assumed			1.330	119.619	.093	.186	-.16178	.12161	-.07900	-.40256

Independent Samples Effect Sizes

		Standardizer ^a	Point Estimate	95% Confidence Interval	
				Lower	Upper
AdoptIntent_Mean	Cohen's d	.68932	.235	-.112	.581
	Hedges' correction	.69343	.233	-.111	.577
	Glass's delta	.76619	.211	-.137	.557

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.

Appendix D: Research question 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.590 ^a	.348	.316	.56948

a. Predictors: (Constant), What is your gender?, To what extent do you agree with the following statement? - I can imagine using a career counseling service., Which age group do you belong to?, Trust_Mean, To what extent do you agree with the following statement about your career situation? - I have already considered a different career path or job profile., To what extent do you agree with the following statement? - I feel familiar with AI tools (Artificial Intelligence).

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.304	6	3.551	10.948	<.001 ^b
	Residual	39.890	123	.324		
	Total	61.194	129			

a. Dependent Variable: AdopIntent_Mean

b. Predictors: (Constant), What is your gender?, To what extent do you agree with the following statement? - I can imagine using a career counseling service., Which age group do you belong to?, Trust_Mean, To what extent do you agree with the following statement about your career situation? - I have already considered a different career path or job profile., To what extent do you agree with the following statement? - I feel familiar with AI tools (Artificial Intelligence).

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)	.947	.502		1.886	.062	-.047	1.940		
	To what extent do you agree with the following statement? - I can imagine using a career counseling service.	.156	.059	.206	2.651	.009	.040	.273	.882	1.134
	To what extent do you agree with the following statement? - I feel familiar with AI tools (Artificial Intelligence).	.156	.058	.212	2.708	.008	.042	.270	.862	1.160
	To what extent do you agree with the following statement about your career situation? - I have already considered a different career path or job profile.	.041	.054	.060	.767	.445	-.065	.148	.880	1.137
	Trust_Mean	.516	.092	.421	5.617	<.001	.334	.698	.942	1.061
	Which age group do you belong to?	-.008	.056	-.010	-.136	.892	-.118	.103	.918	1.089
	What is your gender?	-.072	.094	-.057	-.769	.443	-.259	.114	.950	1.052

a. Dependent Variable: AdopIntent_Mean

Collinearity Diagnostics^a

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	To what extent do you agree with the following statement? - I can imagine using a career counseling service.	To what extent do you agree with the following statement? - I feel familiar with AI tools (Artificial Intelligence).	To what extent do you agree with the following statement about your career situation? - I have already considered a different career path or job profile.	Trust_Mean	Which age group do you belong to?	What is your gender?
1	1	6.586	1.000	.00	.00	.00	.00	.00	.00	.00
	2	.160	6.418	.00	.01	.04	.01	.00	.71	.00
	3	.113	7.618	.00	.01	.03	.02	.00	.06	.79
	4	.065	10.070	.00	.03	.37	.42	.00	.03	.00
	5	.041	12.614	.00	.95	.02	.20	.02	.00	.00
	6	.026	15.904	.02	.00	.36	.30	.46	.05	.08
	7	.008	29.231	.97	.00	.18	.04	.52	.14	.11

a. Dependent Variable: AdopIntent_Mean

E Research Question 2

Correlations

	Adoptintnt_M ean	PU_Mean	PEOU_Mean	Trust_Mean	I feel comfortable sharing personal career history and interest data with an AI tool.
Adoptintnt_Mean	1	.616	.339	.485	.433
		.000	.000	.000	.000
		130	130	130	130
PU_Mean	.616	1	.282	.426	.276
		.000	.001	.000	.001
		130	130	130	130
PEOU_Mean	.339	.282	1	.361	.235
		.000	.001	.000	.007
		130	130	130	130
Trust_Mean	.485	.426	.361	1	.359
		.000	.000	.000	.000
		130	130	130	130
I feel comfortable sharing personal career history and interest data with an AI tool.	.433	.276	.235	.359	1
		.000	.001	.007	.000
		130	130	130	130

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.702 ^a	.493	.477	.49812

a. Predictors: (Constant), To what extent do you agree with the following statement about the AI tool? – I feel comfortable sharing personal career history and interest data with an AI tool., PEOU_Mean, PU_Mean, Trust_Mean

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	30.179	4	7.545	30.407	<.001 ^b
	Residual	31.015	125	.248		
	Total	61.194	129			

a. Dependent Variable: Adoptintnt_Mean

b. Predictors: (Constant), To what extent do you agree with the following statement about the AI tool? – I feel comfortable sharing personal career history and interest data with an AI tool., PEOU_Mean, PU_Mean, Trust_Mean

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.218	.372		.587	.558		
	PU_Mean	.534	.085	.451	6.283	<.001	.786	1.272
	PEOU_Mean	.091	.066	.095	1.372	.173	.841	1.189
	Trust_Mean	.219	.093	.179	2.365	.020	.711	1.407
	I feel comfortable sharing personal career history and interest data with an AI tool.	.158	.049	.222	3.209	.002	.844	1.185

a. Dependent Variable: Adoptintnt_Mean

Collinearity Diagnostics^a

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				
				(Constant)	PU_Mean	PEOU_Mean	Trust_Mean	To what extent do you agree with the following statement about the AI tool? – I feel comfortable sharing personal career history and interest data with an AI tool.
1	1	4.905	1.000	.00	.00	.00	.00	.00
	2	.052	9.739	.02	.01	.04	.01	.96
	3	.022	15.039	.04	.13	.91	.04	.01
	4	.012	20.318	.00	.49	.02	.81	.01
	5	.010	22.273	.94	.36	.02	.15	.01

a. Dependent Variable: Adoptintnt_Mean

Appendix E: Research Question 2

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	I feel comfortable sharing personal career history and interest data with an AI tool.	3.42	130	.971	.085
	I would find it reassuring if my data were automatically deleted after, for example, 30 days.	4.16	130	.888	.078

Paired Samples Correlations

		N	Correlation	Significance	
				One-Sided p	Two-Sided p
Pair 1	I feel comfortable sharing personal career history and interest data with an AI tool. & I would find it reassuring if my data were automatically deleted after, for example, 30 days.	130	-.098	.134	.268

Paired Samples Test

		Mean	Std. Deviation	Paired Differences		t	df	Significance		
				Std. Error Mean	95% Confidence Interval of the Difference			One-Sided p	Two-Sided p	
				Lower	Upper					
Pair 1	To what extent do you agree with the following statement about the AI tool? - I feel comfortable sharing personal career history and interest data with an AI tool. - To what extent do you agree with the following statement about the AI tool? - I would find it reassuring if my data were automatically deleted after, for example, 30 days.	-.738	1.378	.121	-.978	-.499	-6.108	129	<.001	<.001

Paired Samples Effect Sizes

		Cohen's d	Standardizer ^a	Point Estimate	95% Confidence Interval	
					Lower	Upper
Pair 1	To what extent do you agree with the following statement about the AI tool? - I feel comfortable sharing personal career history and interest data with an AI tool. - To what extent do you agree with the following statement about the AI tool? - I would find it reassuring if my data were automatically deleted after, for example, 30 days.		1.378	-.536	-.719	-.351
		Hedges' correction	1.387	-.533	-.715	-.349

a. The denominator used in estimating the effect sizes.
Cohen's d uses the sample standard deviation of the mean difference.
Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

F Research Question 3

High-Engagement

Feature	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Ø Rank Position
1 CV optimization	27	33	16	2	7	12	6	2,89
2 Writing cover letters	21	25	20	3	11	14	9	3,35
3 Preparing for job interviews	23	7	28	7	18	11	9	3,57
4 Tips for onboarding at a new job	7	11	16	24	21	10	14	4,23
5 Salary negotiation	11	9	15	25	21	11	11	4,1
6 Skills gap analysis	9	11	5	17	19	29	13	4,6
7 Coaching for changing industries	5	7	3	25	6	16	41	5,25

Low-Engagement

Feature	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Ø Rank Position
1 CV optimization	7	12	2	1	4	0	1	2,52
2 Writing cover letters	11	5	6	0	2	2	1	2,52
3 Preparing for job interviews	3	3	10	2	4	5	0	3,59
4 Tips for onboarding at a new job	4	2	3	5	6	5	2	4,11
5 Salary negotiation	2	3	3	7	7	2	3	4,19
6 Skills gap analysis	0	2	2	8	2	9	4	4,96
7 Coaching for changing industries	0	0	1	4	2	4	16	6,11

Ranks

	Group_Code	N	Mean Rank	Sum of Ranks
CV Optimization	High	103	66.75	6875.00
	Low	27	60.74	1640.00
	Total	130		

Test Statistics^a

CV Optimization	
Mann-Whitney U	1262.000
Wilcoxon W	1640.000
Z	-.762
Asymp. Sig. (2-tailed)	.446

a. Grouping Variable: Group_Code

Mann-Whitney Test

Ranks

	Group_Code	N	Mean Rank	Sum of Ranks
Cover Letter Writing	High	103	68.69	7075.50
	Low	27	53.31	1439.50
	Total	130		

Test Statistics^a

Cover Letter Writing	
Mann-Whitney U	1067.500
Wilcoxon W	1445.500
Z	-2.014
Asymp. Sig. (2-tailed)	.044

a. Grouping Variable: Group_Code

Mann-Whitney Test

Ranks				
	Group_Code	N	Mean Rank	Sum of Ranks
Preparing for job interviews	High	103	65.50	6746.00
	Low	27	65.52	1769.00
	Total	130		

Test Statistics^a

	Preparing for job interviews
Mann-Whitney U	1390.000
Wilcoxon W	6746.000
Z	-.003
Asymp. Sig. (2-tailed)	.998

a. Grouping Variable: Group_Code

Mann-Whitney Test

Ranks				
	Group_Code	N	Mean Rank	Sum of Ranks
Tips for onboarding at a new job	High	103	65.52	6749.00
	Low	27	65.41	1766.00
	Total	130		

Test Statistics^a

	Tips for onboarding at a new job
Mann-Whitney U	1388.000
Wilcoxon W	1766.000
Z	-.015
Asymp. Sig. (2-tailed)	.988

a. Grouping Variable: Group_Code

Mann-Whitney Test

Ranks				
	Group_Code	N	Mean Rank	Sum of Ranks
Salary negotiation	High	103	65.16	6711.50
	Low	27	66.80	1803.50
	Total	130		

Test Statistics^a

	Salary negotiation
Mann-Whitney U	1355.500
Wilcoxon W	6711.500
Z	-.204
Asymp. Sig. (2-tailed)	.838

a. Grouping Variable: Group_Code

Mann-Whitney Test

		Ranks			
		Group_Code	N	Mean Rank	Sum of Ranks
Coaching for changing industries	High		103	62.21	6407.50
	Low		27	78.06	2107.50
	Total		130		

Test Statistics^a

		Coaching for changing industries
Mann-Whitney U		1051.500
Wilcoxon W		6407.500
Z		-2.054
Asymp. Sig. (2-tailed)		.040

a. Grouping Variable: Group_Code