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ARTIFICIAL INTELLIGENCE IN HIGH INVOLVEMENT SALES AND MARKETING INTERACTIONS: UNDERSTANDING CONSUMER ACCEPTANCE AND USE ALONG THE CONSUMER DECISION JOURNEY

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Abstract

This work project investigates consumer acceptance and use of artificial intelligence (AI) in high-involvement sales and marketing interactions applying the UTAUT2 framework and the Consumer Decision Journey (CDJ) model. Key UTAUT2 predictors, Performance Expectancy, Habit, and Hedonic Motivation, were found to significantly influence Behavioral Intention. AI usage was highest in the Active Evaluation Phase, highlighting critical moments for businesses to engage consumers. Additionally, Age and Effort Expectancy shaped usage patterns, particularly among older users. These findings offer theoretical contributions to technology acceptance research and practical implications for businesses aiming to optimize AI strategies across purchase processes.

Keywords

Artificial Intelligence (AI), Technology Acceptance, UTAUT2 Model, Consumer Decision Journey (CDJ), High-Involvement Purchasing, Sales, Marketing, Consumer Behavior

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List of Abbreviations

AI……...…… Artificial Intelligence

ANOVA……..…….. Analysis of Variance

AR…….……..……... Augmented Reality

B2B…….……..….. Business-to-Business

B2C…….…….……. Business-to-Consumer

CDJ……..……. Consumer Decision Journey

CI…….…….…… Confidence Interval

CRM……..…….. Customer Relationship Management

EFA……..……. Exploratory Factor Analysis

KMO……..……..……. Kaiser-Meyer-Olkin

ROI……..……...……. Return on Investment

SPSS……...……. IBM Statistical Package for the Social Sciences

TAM……...……..… Technology Acceptance Model

U.S. ...…….....…….……. United States

UTAUT……..…….. Unified Theory of Acceptance and Use of Technology

UTAUT2…….……. Unified Theory of Acceptance and Use of Technology 2

VIF……..……...…… Variance Inflation Factor

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1. Introduction

Artificial intelligence (AI) is here to stay and will impact and reshape society at a pace never seen before for many years to come (Luan et al. 2020; McKinsey & Company 2024). Technological advancements involving AI are starting to drastically disrupt industries and life outside of information technology such as manufacturing, production, agriculture, education, services and many more (Luan et al. 2020; Makridakis 2017; Vyhmeister et al. 2022). Mostly, AI is understood as a software product but as for many technical devices' software can drive the function of a hardware product. The underlying project aims to examine which factors influence consumer acceptance and use of AI technologies in high-involvement sales and marketing interactions. In addition, it explores AI interactions in different stages of the Consumer Decision Journey (CDJ). Firstly, the paper grants deeper insight into the current research regarding AI systems in relation to high-involvement purchase behavior. Furthermore, the project aims to deepen existing technology acceptance research by applying and extending the sophisticated Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) construct to the analyzed context. Based on present findings a conceptual framework is carefully derived and backed with research hypotheses which are tested utilizing statistical analysis. The aim of this analysis is to explore how surveyed consumers accept and use AI in high-involvement purchases. The hypotheses are examined for interrelatedness and moderating effects of the variables measured, to thoroughly discuss implications for businesses that aim to employ AI systems when interacting with consumers. This project finds that key UTAUT2 factors significantly drive consumers' behavioral intention to use AI in high-involvement purchase decisions, with Age moderating the role of Hedonic Motivation. AI usage peaks during the Active Evaluation Phase of the CDJ, highlighting critical opportunities for businesses to influence consumer decision-making by leveraging AI systems. Lastly, the findings are discussed and accompanied by research limitations and a final conclusion.

2. Theoretical Background

The theoretical background of this research project clarifies the concept of high-involvement purchase behavior and spotlights the current state of research regarding the usage of AI in sales and marketing, before examining past and current developments regarding the CDJ.

2.1 High-Involvement Purchase Behavior

The comprehension of high-involvement purchase behavior is of utmost importance, as it is central to the underlying research and needs development prior to deeper exploration regarding the relationship of AI in sales and marketing processes. Psychologically seen involvement implies a subjective state reflecting the significance or relevance an individual attributes to an object or occasion (Johnson and Eagly 1990). High-involvement purchases refer to an acquisition, which requires notable consideration, research, and comparison as high stakes are present. Low-involvement purchases on the other hand are typically characterized by daily purchases that exert low financial risk, value and motivation to conduct information research (Spears et al. 2016). Typical cases of high-involvement purchase decisions in research include real estate (Arachchige et al. 2022; Hochstein et al. 2018), cars (Geva et al. 2017; Hochstein et al. 2018) or electronics (Hamilton and Chernev 2013). These transactions are typically characterized by elevated consumer costs. Nonetheless, explorations suggest involvement of more complex factors other than price when consumers commit to such purchases (Arachchige et al. 2022; Geva et al. 2017; Lin 2012). For automotives, consumers seem to demonstrate high levels of involvement throughout the entire buying process, from initial information seeking to post-purchase evaluation (Molesworth and Suortti 2002). This lasting cognition through multiple phases of the purchase decision accentuate the long-term commitment typical for such purchases. Another characteristic high-involvement decisions are subject to is the entanglement of personal relevance, values and norms. Wang and Chou (2020) uncovered that purchasing behavior regarding fair trade products seems partially mediated by personal subjective norms

which form humans attitudes regarding societal responsibilities. The effects of individual values and beliefs, influencing high-involvement purchase decisions are to be further examined. Lastly, it appears that the complexity of a product influences the level of involvement. Even though the availability of online information increases, consumers continuously seek human sales interactions when engaging in high-involvement purchases Hochstein et al. (2018). In summary, there is a clear need for sophisticated AI systems that diminish consumers costs, reduce the risk of long-term investment, align personal relevance and values while additionally minimizing the complexity of purchasing.

2.2 Artificial Intelligence in Sales and Marketing

As mentioned, AI is disrupting and rearranging the way we understand and conduct business at an astonishing pace. A survey by McKinsey & Company from March 2025 found that 78% of respondents stated that their organization leveraged AI in at least one business function. Sales and marketing strategies are subject to unparalleled opportunities granting the ability enrich overall customer experience (Odeibat 2024). Marketeers aim at increasing product sales by carefully targeting their customers by utilizing web-based and AI driven tracking techniques (Goldfarb and Tucker 2011; Huang and Rust 2021). The success of big data initiatives in marketing and sales is not guaranteed. Increasing sales hinges on carefully aligning analytic capabilities with organizational needs, market dynamics, and data maturity. To unlock full potential of AI algorithms, businesses must alter their data strategies to impact consumer behavior. Research by Hao et al. (2019) examined an inverted U-shape relationship for U.S. based innovation projects on big data AI projects, providing evidence that excessive data utilization might be harmful for businesses trying to make considerate and swift decisions. When examining literature on AI in sales and marketing processes the topic of human versus AI agents is a dominant field that requires highlighting in this context. Adam et al. (2022) indicate that customers favor human interaction regarding the initial product exposure, while preferably

engaging with AI agents in the latter stages of the CDJ like appointment scheduling, thus indicating volatility across different purchase stages. A collaborative approach between AI agents and humans seems to leverage the best results. In a series of randomized field experiments from 2020 Luo et al. illustrate that a combined human and AI coaching approach toward sales interactions outperformed both the AI and human agent alone. Additionally, Lou et al. (2020) propose an inverted U-shaped relationship for sales agent coaching. While mid-ranked human sales agents benefit most from the AI coach, top ranked agents show limited gains due to AI aversion, while low ranked agents were subject to information overload. A pressing issue businesses face in AI supported sales and marketing are the notable data privacy challenges. AI usage is subject to extensive collection, processing, and use of personal data, which in turn raises concerns regarding potential privacy breaches and data security risks (Kaissis et al. 2020; Meurisch and Mühlhäuser 2021). Meurisch and Mühlhäuser (2021) stress the fact that although AI enhances personalization and customer engagement, it inherently depends on user data, highlighting a fundamental trade-off between delivering tailored experiences and safeguarding privacy. Data privacy has become a critical global concern, nudging regulatory efforts such as the European Artificial Intelligence Act (AI Act). This act aims to ensure that AI systems are developed and implemented in ways that uphold fundamental rights, including the protection of personal data (European Commission 2024). In summary, the advancement of AI in sales and marketing confronts businesses with both transformative opportunities and pressing challenges. Moving forward, success in this domain will depend on striking a careful balance between technological innovation and responsible data stewardship.

2.3 AI Adoption Across the Consumer Decision Journey

In theory and practice the CDJ serves as framework for comprehension on how consumers evaluate and execute purchasing decisions. This section outlines key stages of the decision-making process and explores different approaches and frameworks in research and business.

Market dynamics are subject to constant change, subsequently frameworks regarding the CDJ also evolve continuously as scholars, researchers, and industry practitioners persistently refine and adapt frameworks to changes in society, behaviors and technological advancements. In academic literature, the terms Consumer Decision Journey and Customer Journey are often used interchangeably, despite subtle distinctions emphasis and breadth. Predominantly, models pursue the generalization of sequential phases consumers endure when engaging with a product, brand or service. A foundational and often referenced framework regarding consumer behavior is the AIDA (Attention, Interest, Desire, Action) model. The understanding of this model is that sensory stimulation drives attention, perceived attractiveness generates interest, perceptions of usefulness and credibility shape consumers desire while the final purchase intention reflects an action. Innovation and technological change have remodeled sales interactions. Businesses must harness a multichannel approach to sales operations to match developments regarding E-commerce, social media and digital technologies such as AI. Change affects the entire CDJ, from initial awareness to post-purchase interactions (Gao and Hongfei 2022). The more intricate macroenvironment demands more sophisticated frameworks (He and Zhang 2022). Hamilton and Chernev (2013) argue that the traditional CDJ is increasingly social, shaped by both human and non-human companions such as AI agents. Proximal others (e.g., close friends or family) exert strong influence, while distal others (e.g., influencers, online reviewers) shape norms and behaviors. The journey no longer seems linear or individual, but more dynamic and interactive (Hamilton and Chernev 2013). An often populated and exploited framework in business practice is a structural architecture developed by McKinsey & Company dating back to the year 2009 (Court et al. 2009). It has been revised and adopted multiple times by McKinsey & Company itself (Edelman and Singer 2015) and others but holds significant weight to this day when spotlighting how marketeers can influence consumers decisions.

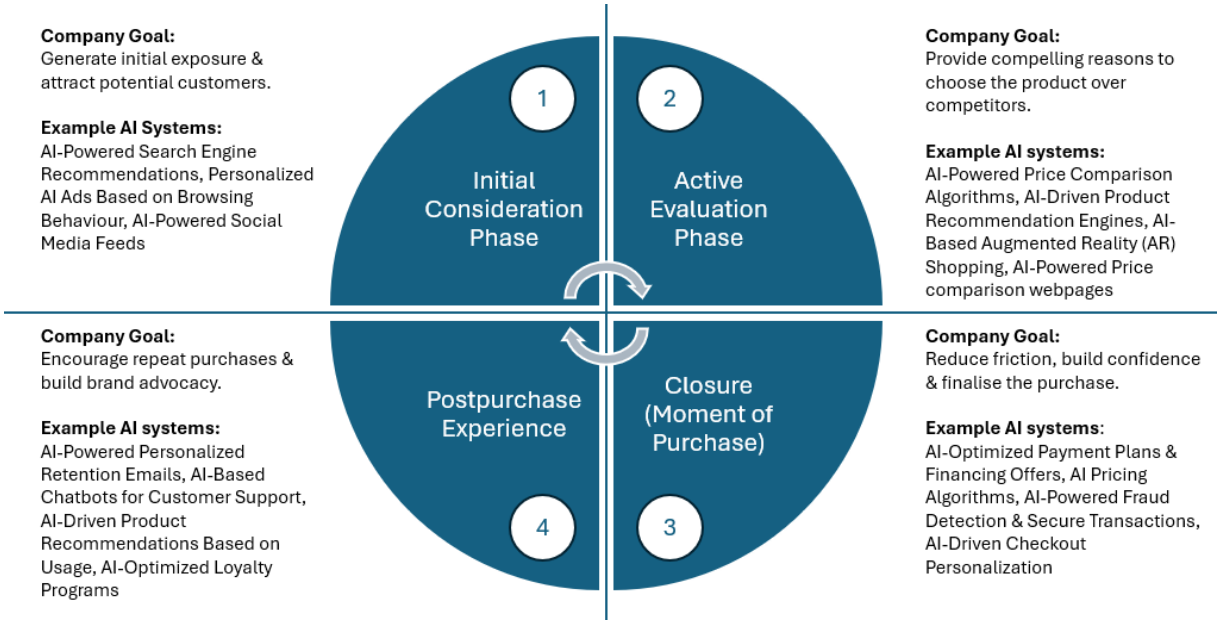

Figure 1: The Circular Consumer Decision Journey (adapted from Court et al. 2009)

This framework serves as central pillar of the underlying research, and the survey presented to participants. The team of consultants at McKinsey & Company reinforce the fact that the CDJ is a circular rather than linear process. The CDJ commences with the Initial Consideration Phase, during which consumers first recognize a need and recall a limited set of brands they already know or trust (Court et al. 2009). At this early stage, brand awareness and visibility are critical. Only a small number of brands make it into the consumer's initial mental shortlist. The primary objective for businesses is to generate initial exposure geared at attracting potential buyers. Research by Unkel and Haas (2017) proposes that consumers trust AI-powered search engine recommendations, as they function as powerful information gatekeepers. Content positioned at the top of the list encounters predominant engagement (Unkel and Haas 2017). Alignment of content with consumer preferences and behavior through AI driven personalization generally yields positive outcomes (Gao et al. 2023). In the Active Evaluation Phase of the CDJ, consumers gather more information, compare alternatives, read reviews, and may add or eliminate brands from their consideration set (Court et al. 2009). Empirical research from the

hospitality industry highlight the crucial influence algorithmically curated social media feeds have in shaping consumer behavior. They serves as facilitators for information sharing and brand interaction in this phase of the decision-making journey (Varkaris und Neuhofer 2017). Particularly in high-involvement purchases where perceived risk is great, high cognitive engagement is eminent. It becomes apparent that businesses must clearly differentiate their offerings while administering compelling reasons for consumers to favor their offering over that of market competitors. AI can play a crucial role here by enhancing decision support. Information-rich, well-structured reviews can significantly enhance trust among highly involved consumers under conditions of perceived risk (Racherla and Friske 2012). Minimizing individual search costs while providing access to multiple offers in one place is an advantage found through AI powered price comparison systems. Listings on such sites can increase the visibility of price options and generally enhances consumer comparison behavior (Ronayne 2021). Additionally, visual cues can guide buying behavior during the Active Evaluation Phase. AI tends to power the intelligence behind augmented reality (AR). A study by Zanger et al. (2022) exhibits that AR meaningfully shapes the evaluation stage of the CDJ by enhancing affective responses, particularly enjoyment and inspiration, which, in turn, positively impact product and brand attitudes, as well as purchase intentions. The Closure Phase also referred to as moment of purchase, represents the final decision and completion of a purchasing transaction, converting intent into action (Court et al. 2009). This phase of the CDJ aims at reducing friction and instilling confidence in consumers. AI enhances pricing accuracy and speeds up decision-making while reducing reliance on subjective judgment by analyzing customer behavior, historical data, and contextual cues (Leung et al. 2019). AI grants businesses novel opportunities, regarding lending and risk assessment offering personalized, data-driven financing options thus improving overall sales efficiency (Herrmann and Masawi 2022). Through real-time analysis of transaction patterns and risk signals (Knuth and Ahrholdt 2022), AI systems foster trust in digital

environments, conclusively encouraging consumers to proceed with online purchases. Stripe, a financial infrastructure platform for businesses, processing $1.4 trillion in payment volume in 2024, leverages AI to create personalized checkout experiences, which contribute to a smoother, more secure, and customer-centric purchase process (Chen and Zhang 2025). Following the purchase of a good or service, consumers enter the Postpurchase CDJ Phase. In this stage of the circular journey a customer interacts with the product. Consumer actively evaluate the overall experience, assess the utility and may indulge in sharing their opinions with others (Court et al. 2009). The general consensus is that this is where brand loyalty, customer retention, and future purchase decisions are formed. A business must focus on fostering repeat purchases and brand advocacy by maintaining engagement and providing customer support, especially in high-involvement contexts. In a digitized sales setting AI facilitates this through personalized signals like retention emails or algorithmically customized retention advertisements. Based on Schweidel et al. (2022), consumer digital signals significantly reshape the CDJ as it enables firms to gather, interpret and execute on behavioral cues. AI-powered customer service chatbots can enhance the overall consumer experience. Chatbots can facilitate informed decision-making and positively influencing postpurchase behavior (Lee and Park 2022). While AI chatbots have shown strong performance in low-involvement decisions, their effectiveness in high-involvement contexts remains unclear (Chen et al. 2023; Klaus and Zaichkowsky 2020). In summary, as AI continues to reshape each stage of the CDJ, both businesses and consumers must actively navigate its integration. Businesses do so by implementing AI responsibly and strategically while consumers must critically engage with AI-driven experiences to ensure informed, value-aligned decision-making.

3. Conceptual Framework and Hypotheses

This section presents the theoretical foundation and conceptual structure that guide the empirical investigation of consumer acceptance and use of AI in high-involvement sales and marketing

interactions. It introduces the UTAUT2 model, which serves as the primary framework for this study. This section further explores all relevant research variables for the specific context of AI-driven sales and marketing interactions. Finally, the hypotheses are derived from the conceptual model, which will be tested through a quantitative research design in the following sections.

3.1 The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

For AI to continuously influence consumer decisions in high-involvement settings across sales and marketing processes, there is a need for overall acceptance and intention of use for these types of technologies and systems. Factors influencing acceptance of technology are multi-faceted and vary across different cultures (Sindermann et al. 2021). One of the most utilized models in modern research is the Technology Acceptance Model (TAM) which has been applied to a variety of technological subsets including AI (Abdekhoda et al. 2014; Al-Adwan et al. 2023; Dogruel et al. 2015; Kim and Garrison 2008; Wang et al. 2023). Within the TAM perceived usefulness and perceived ease of use are the primary determinants of behavioral intention and technology use. To further incorporate additional social and contextual factors, thus offering greater explanatory power across various technology adoption contexts the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. in 2003. The UTAUT model was expanded in a second iteration, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model by Venkatesh et al. in 2012. The UTAUT2 model measures for the constructs Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value and Habit (Venkatesh et al. 2012), making it particularly well-suited for capturing consumer behavior in digitally mediated contexts. As most AI systems grant consumers free comparison, product comprehension and overall utility the predictor Price Value has been excluded. Given the increasing integration of AI technologies in the CDJ the UTAUT2 model provides a comprehensive lens through which to assess the psychological, contextual, and behavioral factors that influence user acceptance. Originally

Venkatesh et al. (2012) applied the UTAUT2 model to assess the behavioral intention and usage behavior regarding mobile internet. The UTAUT model has been extended with further variables in some cases, (Assaker et al. 2019; Bland et al. 2024) while others have combined the research model with further scientific theories, namely the diffusion of innovation model to measure the acceptance and use of fitness wearables (Talukder et al. 2018). As for AI, the UTAUT2 model has been applied in various studies examining the acceptance and use of such technologies. A study in the insurance sector, which is usually linked to high-involvement by Andrés-Sánchez and Gené-Albesa (2023) found that Social Influence most significantly predicted behavioral intention to use AI chatbots, followed by Effort Expectancy. An extended UTAUT model used by Chatterjee et al. (2021) incorporates CRM system quality and user satisfaction as additional predictors, adapting the original UTAUT2 framework to better capture organizational users' intentions to adopt AI-integrated CRM systems. An application of the UTAUT2 model regarding virtual AI assistants by García de Blanes Sebastián et al. (2022) found that habit, trust, and personal innovativeness primarily drive behavioral intention to adopt AI-powered virtual assistants, while traditional UTAUT2 factors like Performance Expectancy, Effort Expectancy and Social Influence, did not significantly impact adoption. In a research paper from 2022 Venkatesh himself states that the UTAUT model should be further developed regarding AI, as this could influence AI adoption in a positive manner and would help to deepen understanding of behavioral intentions (Venkatesh 2022). This underlines the need to further extend research regarding the acceptance and use of AI. Subsequently the UTAUT2 model forms the foundation for the conceptual framework and hypotheses development presented in the following sections.

3.2 Hypotheses

Tough some research papers (Andrés-Sánchez and Gené-Albesa 2023; García de Blanes Sebastián et al. 2022) have touched the topic of high-involvement in regard to AI, their research goals were not clearly aimed at understanding the acceptance and use of AI in high-involvement

consumer purchase decisions. There is a clear lack of research in this field which this underlying study aims to address. Grounded on the extended UTAUT2 model and informed by relevant literature on AI adoption, consumer trust, and high-involvement decision-making, the hypotheses aim to explore the key factors influencing consumer acceptance and use of AI in sales and marketing interactions. Additionally, the survey identifies the usage frequency for AI systems in each phase of the CDJ, to deeper understand the adoption of AI regarding high-involvement purchase decisions. Each hypothesis is designed to test the relationships between theoretical constructs and consumer behavior, providing a structured basis for the quantitative analysis. To further extend and broaden the insights gained through the study the variables age, sex, nationality, education level and overall AI experience were surveyed (Appendix 1). The main hypothesis of the thesis is grounded in UTAUT2 model. It explores how the core predictors of the model shape consumers' behavioral intention to adopt AI technologies in high-involvement purchase decisions and aims to capture the key psychological and contextual drivers of AI acceptance in a complex, decision-intensive setting (Appendix 2).

H1: The UTAUT2 predictors — including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit — significantly influence consumers' Behavioral Intention to use AI in high-involvement purchase decisions.

Research on differences in sex regarding the impact of social influence on technology adoption reveals inconsistent outcomes, while some studies indicate that women are more responsive to social cues, others challenge this assumption, indicating that the relationship may be more context-dependent than previously thought. Nysveen et al. (2005) indicate that female participants are influenced more than males by social norms in terms of mobile chat services adoption. This is supported by findings made by Yang et al. (2009) that female users' intentions to share videos on YouTube were significantly shaped by perceived social norms. Viswanath

Venkatesh proposes that women may place greater value on social feedback, making them more likely to be influenced by the opinions of others when adopting new technologies (Venkatesh 2000). Contradictory to these findings Forgas-Coll et al. (2021) laid out that men were primarily driven by social influence, whereas women placed greater emphasis on perceived enjoyment when deciding to use a robot. A study on peer-to-peer mobile payment acceptance suggests that men may be more sensitive to social influence than women (Kalinić et al. 2019). Given the mixed empirical findings with a slight overweight indicating women are more socially influenced in terms of technology acceptance and use, testing H2 is essential to clarify whether females are indeed more responsive to social cues in the present research context (Appendix 3).

H2: Sex will moderate the relationship between Social Influence and Behavioral Intention to use AI in high-involvement purchase decisions, such that the effect of Social Influence is stronger among females.

Age is a common demographic assessed for moderation when researching technology acceptance. A paper applying the UTAUT2 model to research the adoption of mobile applications for restaurant searches or reservations by consumers found no significant effects of age (Palau-Saumell et al. 2019) while the paper proved that hedonic motivation is a key driver for usage intention. To further deepen research regarding this relationship and the overall effects of age in high-involvement purchase decisions the following hypothesis aims to evaluate this relationship in context of the underlying topic (Appendix 4).

H3: Age moderates the relationship between Hedonic Motivation and Behavioral Intention to use AI in high-involvement purchase decisions, such that the effect is stronger among younger consumers.

Data on the usage frequency of AI services in high-involvement purchase decisions along the

entire CDJ grants the ability to deepen insights for businesses to make more informed decisions when adoption AI systems. By examining the correlation between Behavioral Intention and Cumulated AI Usage Frequency along the CDJ, this study provides insight into whether consumers who express strong intent to use AI also engage with it throughout their personal decision-making process. This connection is particularly important in high-involvement purchase contexts, where intention may not always translate into action due to complexity, trust concerns, or usability barriers. The assumption of H4 is that both research concepts are closely linked, further validating the research model (Appendix 5).

H4: There is a significant positive correlation between consumers' Behavioral Intention to use AI and the Cumulated AI Usage Frequency along all phases of the Consumer Decision Journey.

The dataset grants the ability to identify if there are any significant differences in usage patterns of AI systems across each phase of the CDJ namely the Initial Consideration Phase, Active Evaluation Phase, Closure Phase and the Postpurchase Experience Phase. The goal of H 4.1 is to identify if and to what extent AI usage differs across the CDJ (Appendix 6).

H4.1: There are significant differences in AI usage frequency across the four phases of the Consumer Decision Journey.

As for H3, which researches the acceptance and use of technology in relation to age this independent variable also acts as a potential relationship driver when assessing high-involvement purchase decisions along the CDJ. Older individuals have shown to value privacy over utilization when interacting with AI technologies, additionally showing signs of mistrust towards AI technologies (Fox and Connolly 2018). Other factors identified in research are the lack of technical skills indicating diminished usage due to perceptions of lower self-efficacy (Fox and Connolly 2018; Jøranson et al. 2023) (Appendix 7).

H5: Age negatively influences Cumulated AI Usage Frequency along the entire Consumer Decision Journey, such that older consumers report lower usage of AI systems during high-involvement purchase decisions.

Building on H5 the hypothesis H5.1 combines both variables from the UTAUT2 model and the findings made on the usage frequencies along the CDJ. The focus of H5.1 lies specifically on the Active Evaluation Phase as it represents the crucial process step between initial consideration and the actual purchase intention. Therefore, the variable Effort Expectancy is isolated and applied as mediator for this test. The construct of Effort Expectancy aligns with self-efficacy and thus extends the research made by Fox and Connolly (2018) and further research that found that usability and ease of use are crucial for technology adoption amongst older individuals (Kim and Choudhury 2020; Lee and Coughlin 2014) (Appendix 8).

H5.1 Effort Expectancy mediates the relationship between Age and AI usage frequency in the Active Evaluation Phase, such that older users perceive AI as less easy to use, which reduces their likelihood of utilizing AI systems during this CDJ phase.

4. Methodology

This chapter outlines the methodological framework used to examine the acceptance and usage of AI technologies in high-involvement consumer purchase decisions along the CDJ. It details the research design, data collection procedures, measurement instruments, and analytical methods employed to test the proposed hypotheses. A quantitative, survey-based approach was chosen to capture perceptions, intentions, and behaviors related to AI usage, guided by the UTAUT2 model. This methodology enables the assessment of relationships between theoretical constructs and demographic moderators and mediators, while also exploring behavioral patterns across the distinct phases of the CDJ. The questionnaire was conducted over 14 days in March of 2025 and resulted in a sample of 233 valid answers (Appendix 9). A priori power analysis

utilizing G*Power prove this sample size to be sufficient for all tests conducted (Appendix 10). Reliability analyses were conducted for each UTAUT2 construct individually, as they represent conceptually distinct factors within the theoretical framework. Internal consistency was assessed using Cronbach's alpha, with all scales demonstrating acceptable reliability of $\alpha \geq .70$ (Taber 2017) (Appendix 11). Since the four CDJ phases represent distinct stages of a sequential process, internal consistency was not assessed. Face validity was established using well-documented and previously validated measurement scales drawn from the UTAUT2 model (Venkatesh et al. 2012) which has been extensively applied in information systems and technology acceptance research. Each item was reframed to high-involvement purchase decisions and selected to align clearly with its intended construct, ensuring that the survey questions accurately measure the theoretical dimensions they were designed to assess. In addition to establishing face validity with established UTAUT2 measurement items, convergent validity was assessed using an Exploratory Factor Analysis (EFA) with Principal Axis Factoring and Varimax rotation (Appendix 12). The EFA revealed a clear and coherent five-factor structure aligning with the theoretical dimensions of the UTAUT2 model confirming internal consistency and construct alignment. The Kaiser-Meyer-Olkin (KMO) value of .883 indicates good sampling adequacy, and Bartlett's Test of Sphericity was significant ($\chi^2 = 2998.196$, $p < .001$), confirming the factorability of the correlation matrix (Howard 2016). The recommended satisfactory variable load onto their primary factor above 0.40 was fulfilled for all variables (Howard 2016). Although the EFA indicated that items related to Performance Expectancy and Effort Expectancy loaded on a single underlying factor, the two constructs were retained and analyzed separately in alignment with the UTAUT2 model by Venkatesh et al. (2012). Theoretical distinctions between the constructs justify this separation. Performance Expectancy reflects the perceived usefulness and outcome related benefits of using AI systems in high-involvement purchase decisions, whereas Effort Expectancy captures the perceived ease of use and clarity in interacting with such

systems. Research objectivity was maintained by using standardized, validated instruments and automated statistical procedures (SPSS and PROCESS 4.2). All analyses were conducted independently of personal interpretation, ensuring replicability and methodological transparency. The descriptive statistics for all relevant variables can be found in the Appendix 13. Analysis of descriptive statistics for skewness and kurtosis indicated that most variables fall within acceptable ranges of ±1.0 for skewness and ±2.0 for kurtosis (Hair et al. 2021). These findings support the assumption of approximate normality for the dependent variables, validating the use of parametric procedures for analysis.

5. Results

The following sections provide results from correlation analysis, multiple and moderated regression models, mediation analysis, and repeated-measures ANOVA, each aligned with the hypotheses outlined in Chapter 3.3.

5.1 Results Hypothesis 1

A multiple linear regression was conducted to assess whether the UTAUT2 predictors significantly influence consumers' behavioral intention to use AI in high-involvement purchase decisions. The overall model was statistically significant, $F(6, 226) = 87.45$, $p < .001$, and explained 69.1% of the variance in Behavioral Intention (adjusted $R^2 = .691$) (Appendix 14). The predictors, Performance Expectancy ($\beta = .431$, $p < .001$), Hedonic Motivation ($\beta = .192$, $p < .001$), Habit ($\beta = .356$, $p < .001$) and Facilitating Conditions ($\beta = .087$, $p = .044$) were found to significantly influence Behavioral Intention towards AI systems in high-involvement purchase scenarios. Effort Expectancy ($\beta = –.019$, $p = .702$) and Social Influence ($\beta = –.002$, $p = .964$) did not show statistically significant effects (Appendix 15). No multicollinearity issues were detected as all VIF values were < 2.052 (O'Brien 2007). These results partially support Hypothesis 1, suggesting that specific UTAUT2 predictors play a role in shaping consumer behavioral intention toward AI in high-involvement purchasing contexts.

5.2 Results Hypothesis 2

To test Hypothesis 2, a moderation analysis was conducted using PROCESS 4.2 Model 1 (Hayes 2012), with Social Influence as the independent variable, Sex as the moderator and Behavioral Intention as the dependent variable. The model was statistically significant, $F(3, 229) = 23.14$, $p < .001$, explaining 23.3% of the variance in Behavioral Intention ($R^2 = .233$). Social Influence had a statistically significant positive effect on Behavioral Intention ($B = 0.520$, $p < .001$) when it is not adjusted for the other predictors of the UTAUT2 model. However, the main effect of Sex was not significant ($b = – 0.006$, $p = .967$) and more importantly the interaction between Social Influence and Sex was not statistically significant either ($b = – 0.076$, $p = .510$), indicating that the strength of this relationship did not differ between males and females (Appendix 16). Therefore, Hypothesis 2 was not supported.

5.3 Results Hypothesis 3

To test Hypothesis 3, a moderation analysis was conducted using PROCESS 4.2 Model 1 (Hayes 2012), with Hedonic Motivation as the independent variable, Age as the moderator and Behavioral Intention as the dependent variable. The model was statistically significant, $F(3, 229) = 38.07$, $p < .001$, explaining 33.3% of the variance in Behavioral Intention ($R^2 = .333$). The main effect of Hedonic Motivation on Behavioral Intention was positive and significant ($b = .658$, $p < .001$), suggesting that greater enjoyment in using AI is associated with higher intention to use it. The main effect of Age was not significant ($b = .0126$, $p = .141$), but the interaction between Hedonic Motivation and Age was significant ($b = .0161$, $p = .014$). This supports the presence of a small moderation effect. Conditional effects analysis showed that at lower age levels (e.g., 23.44 years — 16th percentile), the effect of Hedonic Motivation on Behavioral Intention was $b = 0.5549$, $p < .001$, whereas at median age (26 years — 50th percentile), the effect increased slightly to $b = 0.5962$, $p < .001$, and at higher age levels (34 years — 84th percentile), the effect further increased to $b = 0.7250$, $p < .001$. These results suggest that as age

increases, the positive association between Hedonic Motivation and Behavioral Intention strengthens. Contrary to the original hypothesis, the moderation effect was observed in the opposite direction: Hedonic Motivation exerted a stronger influence on Behavioral Intention among older consumers rather than younger ones (Appendix 17). Consequently, while a moderation effect was detected, Hypothesis 3 is only partially supported.

5.4 Results Hypothesis 4

Hypothesis 4 utilized a Pearson correlation analysis which was conducted examining the relationship between consumers' Behavioral Intention to use AI and the Cumulated AI Usage Frequency of AI along all phases of the CDJ. Results revealed a large and statistically significant positive correlation, $r\,(233) = .611, p < .001$ (Cohen 1992) (Appendix 18). The strong correlation between Behavioral Intention and Cumulated AI Usage Frequency not only confirms Hypothesis 4 but also provides further validity regarding the relationship of the overall conceptual framework guiding the underlying research.

5.5 Results Hypothesis 4.1

A repeated-measures ANOVA was conducted to examine differences in AI usage frequency across the four phases of the CDJ. The analysis revealed a statistically significant overall effect, $F(3, 696) = 38.626, p < .001$, with a large effect size of $\eta^2_p = .143$ (Cohen 1992), indicating that AI usage frequency significantly varied across the phases (Appendix 19). Sphericity violations uncovered through Mauchly´s Test were corrected utilizing the Greenhouse Geisser correction (Appendix 19). Pairwise comparisons showed that the Active Evaluation Phase had significantly higher AI usage than the Initial Consideration Phase (mean difference = 0.197, $p = .038$), the Closure/Purchase Phase (mean difference = 0.738, $p < .001$), and the Postpurchase Phase (mean difference = 0.665, $p < .001$). No significant difference was observed between the Closure Phase and the Postpurchase Phase (mean difference = 0.073, $p = 1.000$) (Appendix 20). Based on the estimated marginal means, AI usage was highest during the Active Evaluation Phase ($M = 3.03$),

followed by the Initial Consideration Phase (M = 2.83), the Postpurchase Experience Phase (M = 2.36), and was lowest during the Closure Phase (M = 2.24) (Appendix 21). These findings emphasize relevant implications for businesses that utilize AI systems discussed later in this study.

5.6 Results Hypothesis 5

To test Hypothesis 5, a simple linear regression analysis was conducted to examine whether Age negatively influences consumers' Cumulated AI Usage Frequency along all phases of the CDJ. The results revealed that age was not a significant predictor of AI usage frequency, $F(1, 231) = 1.247$, $p = .265$, (adjusted $R^2 = .001$). Although the standardized regression coefficient indicated a slight negative relationship ($\beta = -0.073$, $p = .265$), this relationship was not statistically significant (Appendix 22). Consequently, Hypothesis 5 is rejected suggesting that, contrary to expectations, Age does not significantly predict Cumulated AI Usage Frequency during high-involvement purchases along the CDJ.

5.7 Results Hypothesis 5.1

Given the lack of a direct significant relationship between Age and Cumulated AI Usage Frequency, Hypothesis 5.1 further explores whether this relationship may instead be mediated by Effort Expectancy, particularly during the Active Evaluation phase of the CDJ. A mediation analysis using PROCESS 4.2 Model 4 (Hayes 2012) was conducted to examine whether Effort Expectancy mediates the relationship between Age and AI usage frequency during the Active Evaluation Phase of the CDJ. The analysis revealed that Age had a significant negative effect on Effort Expectancy ($b = -0.0281$, $p < .001$) indicating that older participants perceived AI systems as less easy to use. In turn, Effort Expectancy had a significant positive effect on AI usage frequency during the Active Evaluation Phase ($b = 0.5424$, $p < .001$). The direct effect of age on AI usage frequency, when controlling for Effort Expectancy, was not significant ($b = 0.0057$, $p = .4684$). Importantly, the indirect effect of age on AI usage frequency through Effort

Expectancy was significant (b = −0.0152) with a 95% bootstrapped *CI* [-0.0249, -0.0074], excluding zero. This finding supports Hypothesis 5.1 and indicates that older consumers are less likely to use AI tools during Active Evaluation primarily because they perceive AI systems as less easy to use even though the effect represents a small mediation effect (Appendix 23).

6. Discussion

The findings made in the underlying research project grant meaningful insights on the acceptance and use of AI technologies in high-involvement consumer purchase decisions. Grounded in the UTAUT2 model and the CDJ the findings support established research made on consumer behavior. The results confirm the relevance of several key constructs and uncover critical nuances that deepen and extend general understanding of consumer decisions in high-risk settings. In addition, the observations made can be translated into practical implications for businesses, sales operators and marketeers. Furthermore, the conceptual structure of the present study that guided the empirical investigation serves as stable a foundation for future research aimed at validating the acceptance and use of AI and other technologies along the CDJ. The main research hypothesis H1 was partially confirmed. Performance Expectancy, Hedonic Motivation, Habit and Facilitating Conditions were shown to significantly influence Behavioral Intention to use AI systems in high-involvement settings. Effort Expectancy and Social Influence did not prompt significant results and therefore need more nuanced investigation going forward. The findings in H1 align with Venkatesh et al. (2012), who emphasized the centrality of Performance Expectancy in predicting intention. Further, the results propose that for high-involvement purchases, intrinsic factors such as enjoyment and established habits are prioritized over ease of use or external social opinions. When high consumers costs, risk, long-term commitment and personal values are on the line, it seems evident that consumers aim for uniqueness, social distinction and sovereignty when making purchase decisions. The non-significant effects for Effort Expectancy could also reflect the complexity involved when using

AI systems, consumers would rather trust their habitual patterns, than engaging with technologies they do not fully comprehend. Interestingly, H2, examining the moderating effect of Sex on the relationship between Social Influence and Behavioral Intention was not supported, despite previous literature leaning more towards effects on the side of women. This repeatedly highlights the importance of subjective values and self-efficacy when making high-involvement decisions. Hypothesis 3 yielded unexpected yet intriguing findings that might be subject to limitations laid out later. Contrary to the original expectation that younger consumers would be more driven by Hedonic Motivation, the analysis revealed that older consumers experienced a stronger positive effect of enjoyment regarding Behavioral Intention towards AI systems. This result, although small in magnitude, signals a shift in the digital engagement of older individuals. The understanding is that older individuals increasingly value intuitive, emotionally rewarding interactions when navigating complex purchases decisions rather than being exposed to a vast set of options that foster stress, uncertainty and discomfort in the decision-making process. Building on sophisticated frameworks valuable behavioral patterns across the CDJ were also identified. H4 confirmed a strong correlation between Behavioral Intention and Cumulated AI Usage Frequency along the entire CDJ. This reinforces the theoretical assumption that intention is a valid predictor for behavior in high-involvement purchasing contexts. The execution of the repeated-measures ANOVA for Hypothesis 4.1 revealed significant differences in AI usage across the CDJ phases, with usage for AI systems peaking during the Active Evaluation Phase. This reflects the pivotal role that AI can play in supporting cognitive processes such as comparison, research and decision support which all reflect activities central to purchase evaluation. H5, which anticipated a direct negative effect of age on Cumulated AI Usage Frequency, was not supported. However, H5.1 provided a more nuanced understanding: Effort Expectancy mediated the relationship between Age and AI usage in the Active Evaluation Phase. Older users perceived AI systems as more difficult to use, which in turn reduced their

engagement in the highlighted phase. This points out the importance of user-centered AI design and suggests that reducing system complexity could encourage broader adoption. Overall, the findings extend the UTAUT2 model and display a successful integration into a multi-phase structure provided by the CDJ, administering insights between psychological predictors and journey stage. Moreover, they suggest important implications for businesses: to optimize AI-driven strategies, firms must focus not only on technology features but also on demographic sensitivities and journey-based engagement, most importantly when high stakes are involved.

6.1 Business Implications and Future Research

The insights from this study present actionable implications for B2C companies operating in industries with high-involvement products such as real estate, electronics, automotive, finance and insurance. The strong influence of Performance Expectancy, Habit, and Hedonic Motivation highlights the need for AI interactions that are not only functionally effective but also promote habits and enjoyment. Successful businesses will need to emphasize developing AI consumer touchpoints that facilitate comparison, provide meaningful and tailored content while integrating seamlessly into consumer routines. Judgements made in H4.1 that the Active Evaluation Phase was identified as the most AI-intensive stage of the CDJ, confirm that corporations should prioritize investments in AI tools that support research, product discovery and comparison, namely intelligent recommendation engines, chatbots trained on detailed product knowledge and AR experiences for immersive visual exploration. Lower engagement in phases such as the Closure and Postpurchase Phases disclose vast opportunities for optimization. Converting consumers intentions into monetary value will depend on the strategic application of AI in the checkout process, post-sale follow-ups and AI driven consumer loyalty-building. Outcomes in H5.1 call for careful consumer segmentation strategies and understanding of personalized user journeys encouraging adoption amongst all customer groups. Noticeably, the conceptual structure that guided the underlying research could also be applied to B2B business settings.

Enterprise management software, cybersecurity, industrial machinery, commercial real estate infrastructure, telecommunication, sustainability and energy products are all examples of high-involvement B2B product segments that typically involve high financial stakes, complexity, risk and long decision-making cycles. Similar to the CDJ, business decision-makers undergo phases of awareness, evaluation, justification, and implementation. AI solutions aimed at this audience should enhance performance clarity, reduce perceived complexity, and build trust during all phases. For instance, AI-driven product demos, customized ROI simulations and post-deployment onboarding and support chatbots could increase utility for businesses worldwide. Additionally, AI could help B2B sales and marketing teams prioritize high-quality leads based on behavioral data supplying dynamic content personalization to customers while utilizing real-time AI pricing optimization to strike conversions. Furthermore, businesses should consider integrating AI ethics and data transparency into their customer-facing solutions to foster trust and long-term engagement. As regulatory frameworks such as the European AI Act continue to evolve, compliance and ethical design will become key differentiators in shaping consumer acceptance. The variable of trust could be prioritized more extensively in further research settings. In all business contexts, cross-functional alignment between marketing, sales and data science teams will be essential to deploy AI tools that are not only effective but also aligned with strategic brand values. The extension and further validation of phase-specific high-involvement research in both B2C and B2B settings, represent daring and insightful opportunities for businesses, scholars, researchers, and industry practitioners.

7. Limitations

Though the study generated valuable insights regarding high-involvement consumer behavior and AI usage intention across a multiphase model this study is exposed to considerable limitations that will be highlighted in the following section. Firstly, the research scope lacks overall causal validation as it represents a cross-sectional data collection method meaning that

all data is gathered at a single point in time rather than over a longer periods which would grant deeper insights into actual behavioral patterns towards AI and their developmental changes over time. Additionally, the study is faced with limitations related to participant bias. The reliance on self-reported data, particularly for AI usage frequency raises the possibility of recall bias or social desirability effects. Participants potentially over- or understated their actual engagement with AI systems across the CDJ and are not actively confronted with an actual high-involvement decision. An experimental design tracking actual usage while exposing participants to an AI systems would offer a more valid measure of usage and behavioral intention. Furthermore, the research would benefit from additional geographic and cultural validation (Appendix 9.4). Most participants share similar regional, linguistic and cultural contexts. External validity of the findings beyond this population remains uncertain and need further validation. Differences in technology acceptance and usage are known to vary across cultures, markets and regulatory environments. Subsequently, replicating the study across diverse geographic and cultural samples would enhance the robustness of the model. Lastly, the sample itself exhibits demographic skewness and kurtosis, particularly with respect to age. This constitutes an urgent concern as sample is disproportionately composed of younger participants (M = 29.82, SD = 10.70), which may not accurately reflect the attitudes and usage patterns of older consumer groups. Consequently, the generalizability of the findings, especially for age-related hypotheses H3 and H5.1 are limited. Due to the underlying skewness and kurtosis, age had to be treated as a linear, continuous variable. This may have concealed potential nonlinear or generational effects. Future research must focus on a more diverse age distribution to uncover more nuanced behavioral patterns. While the proposed model offers valuable insights into AI acceptance in high-involvement consumer purchase decisions, it has only been tested within the specific context of this study. As such, its transferability across other technologies and domains remains uncertain. Further validation is needed across different research settings and broader fields of

technology acceptance, to determine whether the relationships observed hold true for other disciplines and populations.

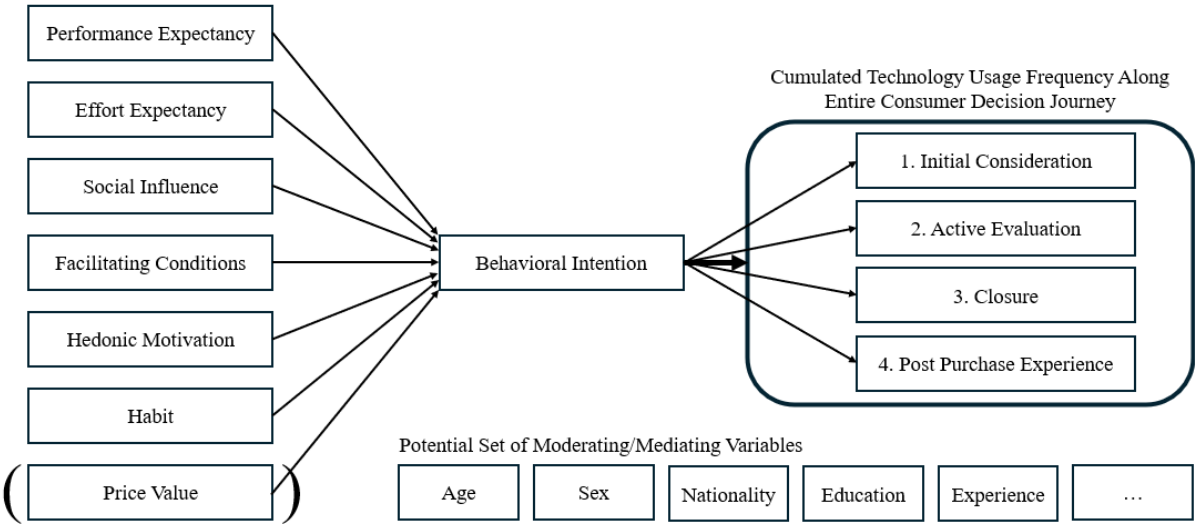

Figure 2 Proposed Scientific Model Combining UTAUT2 and Multi-Phase CDJ Structure

8. Conclusion

The present research successfully explored the acceptance and use of AI technologies in high-involvement purchase decisions by hybrid application of the sophisticated UTAUT2 and CDJ models. The findings confirm that constructs such as Performance Expectancy, Hedonic Motivation and Habit significantly influence Behavioral Intention towards AI. The usage of AI systems was found to be most frequent during the Active Evaluation Phase, suggesting that consumers rely heavily on AI when comparing and assessing alternatives in high personal risk decisions. These valuable insights contribute to both theory and business practice by highlighting stage-specific AI engagement and demographic differences in consumer motivation and usage. While the findings offer valuable guidance, they remain limited to the specific research setting. Future studies are necessary to test the model validity across various technology sets and consumer purchasing domains to broaden its generalizability.

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Appendix

Appendix 1: Distributed Survey

Introduction

Welcome & Thank You for Your Participation!

Dear participant,

thank you for taking the time to participate in this underlying study.
This questionnaire is part of my master's thesis project at Nova School of Business and Economics.

Your insights are invaluable in advancing research on AI acceptance in high involvement sales and marketing interactions along the consumer decision journey.

The focus lies on researching consumers behavioural intention, decision-making and use behaviour when interacting with AI-driven sales and marketing systems.

Anonymity & Data Protection

Your responses will remain completely anonymous and will be used solely for academic purposes. All data will be handled in accordance with EU GDPR (General Data Protection Regulation) guidelines. By entering your email for the Amazon voucher raffle, you agree to be contacted

if you win. All email addresses will be permanently deleted after the raffle is completed.

What to Expect

This survey will take approximately 4-5 minutes to complete.
There are no right or wrong answers—please respond as honestly as possible based on your personal experiences and perceptions.

If you have any questions or concerns, feel free to contact me at 61466@novasbe.pt.
Thank you again for your time and support!

Best regards,
Sean Hornecker
Student - Master's in Management
Nova School of Business and Economics

If you wish to participate in the 50€ Amazon voucher raffle, please enter your E-Mail below.

Demographics

Demographics

To better understand how consumers perceive and interact with AI-driven sales and marketing systems, it is important to consider demographic factors such as age, sex, nationality and education level.

Please indicate your numeric age in years

Please indicate your sex

- ○ Female
- ○ Male
- ○ No specification
- ○ Other

Please indicate your nationality

What is the highest level of education you have completed?

- ○ No formal education
- ○ Primary school
- ○ High school / Secondary education
- ○ Vocational training / Technical diploma / Apprenticeship
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctorate (Ph.D.) or equivalent
- ○ [ ] Other

Overall Experience with AI

AI systems

An **AI system** is an intelligent machine that performs tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language processing.

How would you rate your perceived overall experience with AI systems?

	no experience	very little experience	some experience	considerable experience	extensive experience	expert-level experience
I have ... with AI overall	○	○	○	○	○	○

Usage Frequency

Understanding High-Involvement Consumer Purchase Decisions

Before we continue, it is important to clarify the concept of high-involvement purchases, as it is central to this study.

A high-involvement purchase refers to a buying decision that requires significant consideration, research, and comparison before making a final choice due to the high stakes present. These purchases typically involve:

- High cost (e.g., cars, real estate, premium electronics)

- Long-term commitment (e.g., insurance policies, financial investments)

- Personal relevance (e.g., healthcare plans, higher education)

- Complexity (e.g., customized technology solutions, financial services)

If you have any questions about the concept, feel free to reach out to 61466@novasbe.pt before proceeding with the survey.

Your Personal Consumer Decision Journey

The Consumer Decision Journey, is dynamic, circular process that captures how consumers interact with brands.

McKinsey & Company. (2009). The consumer decision journey. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-consumer-decision-journey

Task: Please choose your usage frequency for AI systems in each phase of the Consumer Decision Journey when making high involvement purchase decisions.

Initial Consideration Phase

When a consumer first thinks about making a purchase, they recall a limited set of brands they already know and trust.

Company Goal: Generate initial exposure & attract potential customers.

Example AI systems: AI-Powered Search Engine Recommendations, Personalized AI Ads based on browsing behaviour, AI-Powered Social Media Feeds

	never	rarely	occasionally	frequently	very frequently	always
I ... use AI systems in the initial consideration phase of my purchase decision.	○	○	○	○	○	○

Active Evaluation Phase

During this stage, consumers gather information, compare options, read reviews, and might even add or remove brands from their consideration set.

Company Goal: Provide compelling reasons to choose the product over competitors.

Example AI systems: AI-Powered Price Comparison Algorithms, AI-Driven Product Recommendation Engines, AI-Based Augmented Reality (AR) Shopping, AI-Powered Price comparison webpages

	never	rarely	occasionally	frequently	very frequently	always
I ... use AI systems in the active evaluation phase of my purchase decision.	○	○	○	○	○	○

Closure - Moment of Purchase Phase

The consumer makes a final decision and completes the purchase.

Company Goal: Reduce friction, build confidence & finalise the purchase.

Example AI systems: AI-Optimized Payment Plans & Financing Offers, AI Pricing Algorithms, AI-Powered Fraud Detection & Secure Transactions, AI-Driven Checkout Personalization

	never	rarely	occasionally	frequently	very frequently	always
I ... use AI systems in the closure phase of my purchase decision.	○	○	○	○	○	○

Postpurchase Experience Phase

After buying, consumers reflect on their decision, interact with the product, and might share their experience with others, which influences future purchases.

Company Goal: Encourage repeat purchases & build brand advocacy.

Example AI systems: AI-Powered Personalized Retention Emails, AI-Based Chatbots for Customer Support, AI-Driven Product Recommendations Based on Usage, AI-Optimized Loyalty Programs

	never	rarely	occasionally	frequently	very frequently	always
I ... use AI systems in the postpurchase phase of my purchase decision.	○	○	○	○	○	○

UTAUT-2

Acceptance and Use of AI Technology in High-Involvement Consumer Purchase Decisions

The final part of this study examines your personal acceptance and use of AI technology in high involvement purchase decisions based on the UTAUT-2 (Unified Theory of Acceptance and Use of Technology 2) model which is frequently applied information technology and digital transformation research.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412

Performance Expectancy

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
I find AI systems useful in my daily life when making high involvement purchase decisions.	○	○	○	○	○	○
Using AI systems helps me accomplish things more quickly when making high involvement purchase decisions.	○	○	○	○	○	○
I confirm that I am paying attention by selecting 'agree' for this question.	○	○	○	○	○	○
Using AI systems increases my productivity when making high involvement purchase decisions.	○	○	○	○	○	○

Effort Expectancy

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
Learning how to use AI systems to make high involvement purchase decisions is easy for me.	○	○	○	○	○	○
My interaction with AI systems when making high involvement purchase decisions is clear and understandable.	○	○	○	○	○	○
I find AI systems for making high involvement purchase decisions easy to use.	○	○	○	○	○	○
It is easy for me to become skilful at using AI systems for high involvement purchase decisions.	○	○	○	○	○	○

Social Influence

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
People who are important to me think that I should use AI systems to make high involvement purchase decisions.	○	○	○	○	○	○

People who influence my behaviour think that I should use AI systems to make high involvement purchase decisions.	○	○	○	○	○	○
People whose opinions that I value prefer that I use AI systems to make high involvement purchase decisions.	○	○	○	○	○	○

Facilitating Conditions

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
I have the resources necessary to use AI systems in high involvement purchase decisions.	○	○	○	○	○	○

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
I have the knowledge necessary to use AI systems in high involvement purchase decisions.	○	○	○	○	○	○
AI systems are compatible with other technologies I use when making high involvement purchase decisions.	○	○	○	○	○	○

I can get help from others when I have difficulties using AI systems in high involvement purchase decisions.	○	○	○	○	○	○

Hedonic Motivation

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
Using AI systems in high involvement purchase decisions is fun.	○	○	○	○	○	○

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
Using AI systems in high involvement purchase decisions is enjoyable.	○	○	○	○	○	○
Using AI systems in high involvement purchase decisions is very entertaining.	○	○	○	○	○	○

Habit

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
The use of AI systems in high involvement purchase decisions has become a habit for me.	○	○	○	○	○	○

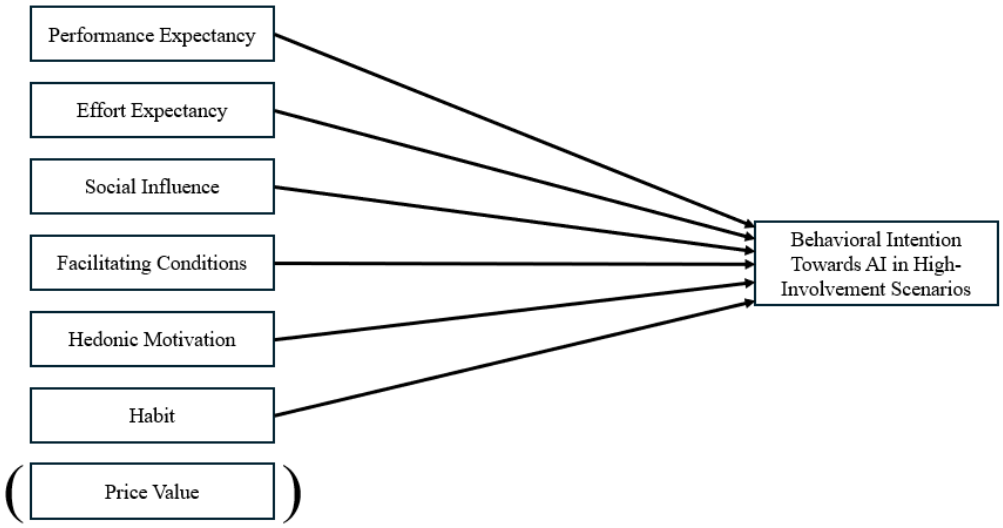
I am addicted to using AI systems in high involvement purchase decisions.	○	○	○	○	○	○

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
I must use AI systems in high involvement purchase decisions.	○	○	○	○	○	○

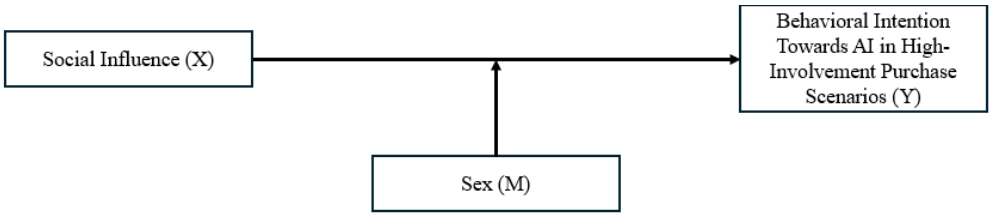
Behavioural Intention

	strongly disagree	disagree	somewhat disagree	somewhat agree	agree	strongly agree
I intend to continue using AI systems in high involvement purchase decisions in the future.	○	○	○	○	○	○
I will always try to use AI systems in high involvement purchase decisions in my daily life.	○	○	○	○	○	○
I plan to continue to use AI systems in high involvement purchase decisions frequently.	○	○	○	○	○	○

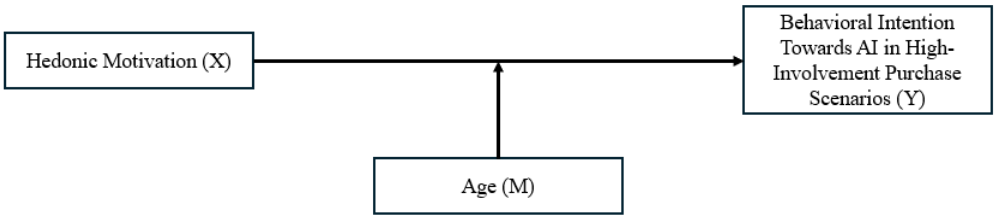
Appendix 2: Scientific Research Model UTAUT2 Variables Hypothesis 1



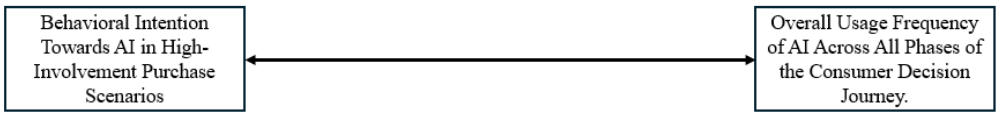
Appendix 3: Scientific Research Model Hypothesis 2



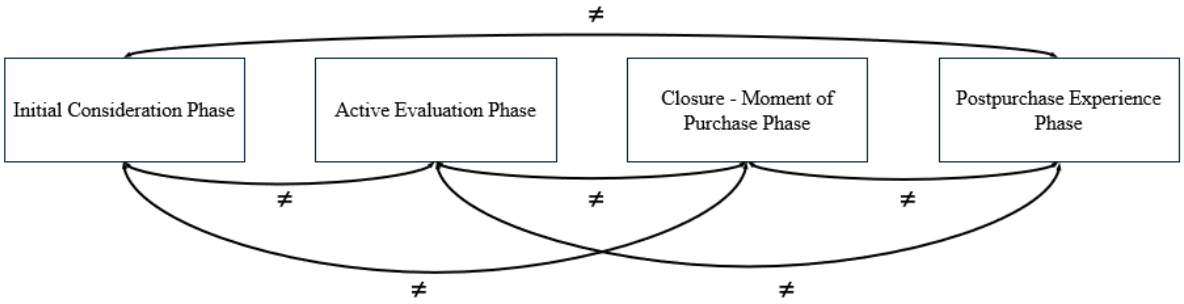
Appendix 4: Scientific Research Model Hypothesis 3



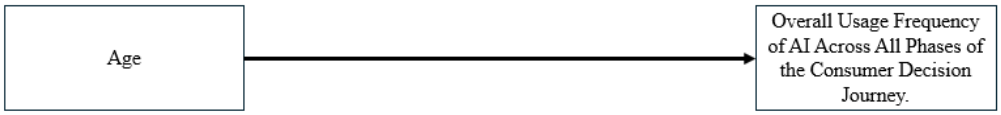
Appendix 5: Scientific Research Model Hypothesis 4



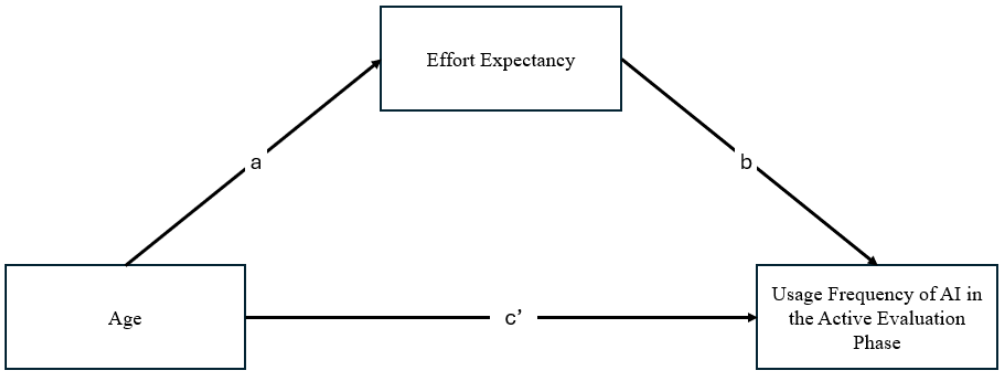
Appendix 6: Scientific Research Model Hypothesis 4.1



Appendix 7: Scientific Research Model Hypothesis 5



Appendix 8: Scientific Research Model Hypothesis 5.1



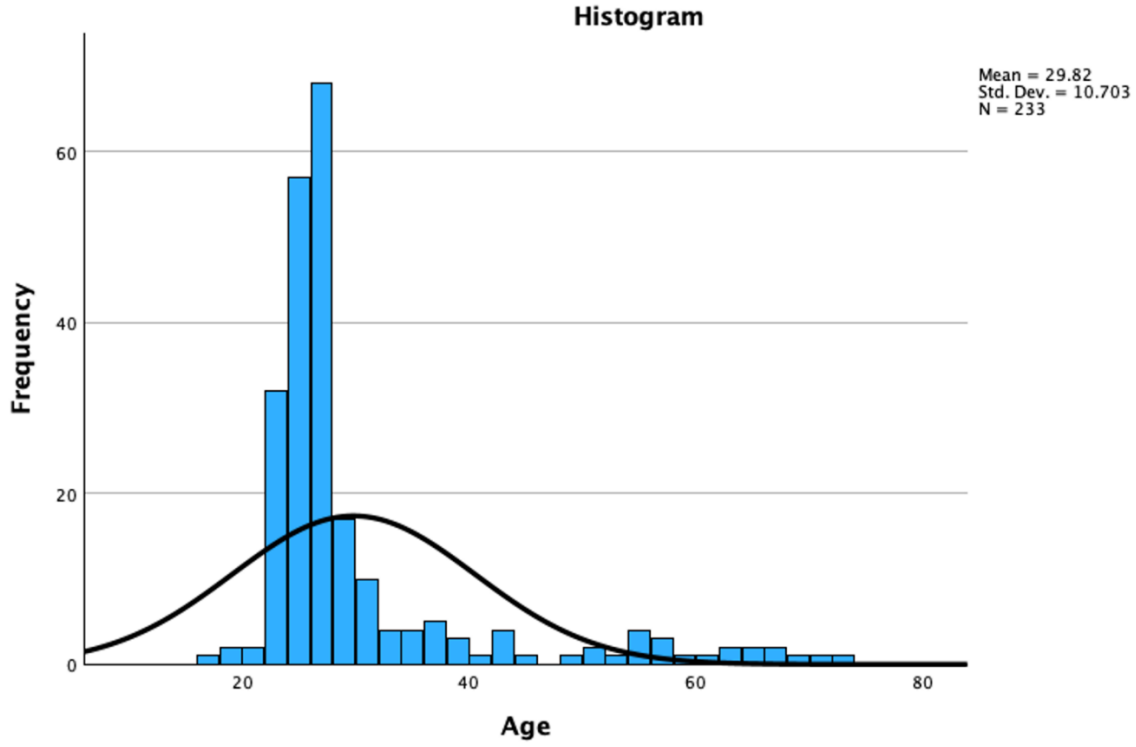
Appendix 9: Descriptive Statistics of the Sample

Appendix 9.1: Descriptive Statistics Sample Age Distribution

Age Statistics

Age

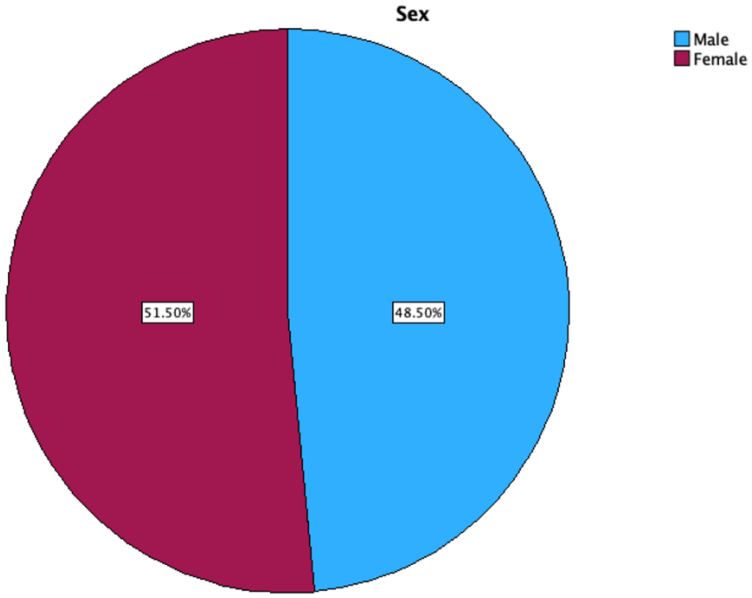
N	Valid	233
	Missing	0
Mean		29.82
Median		26.00
Std. Deviation		10.703
Variance		114.545
Skewness		2.340
Std. Error of Skewness		.159
Kurtosis		4.820
Std. Error of Kurtosis		.318
Range		55
Minimum		17
Maximum		72
Percentiles	16	23.44
	50	26.00
	84	34.00



Appendix 9.2: Descriptive Statistics Sample Sex Distribution

Sex

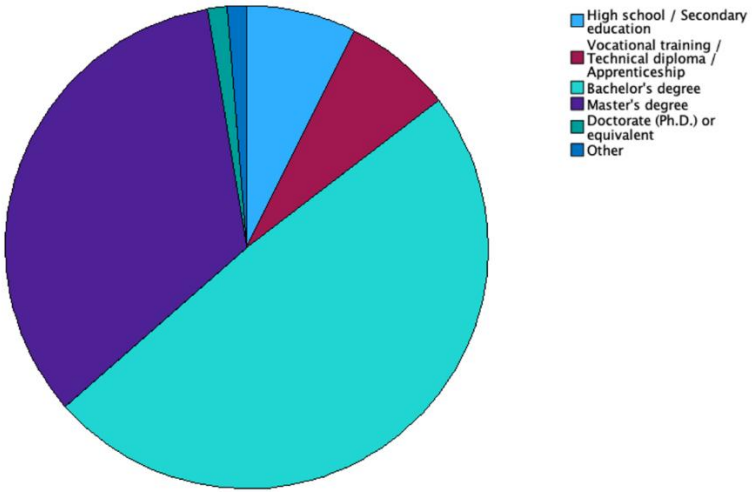
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	113	48.5	48.5	48.5
	Female	120	51.5	51.5	100.0
	Total	233	100.0	100.0	



Appendix 9.3: Descriptive Statistics Sample Education Distribution

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school / Secondary education	17	7.3	7.3	7.3
	Vocational training / Technical diploma / Apprenticeship	17	7.3	7.3	14.6
	Bachelor's degree	114	48.9	48.9	63.5
	Master's degree	79	33.9	33.9	97.4
	Doctorate (Ph.D.) or equivalent	3	1.3	1.3	98.7
	Other	3	1.3	1.3	100.0
	Total	233	100.0	100.0	



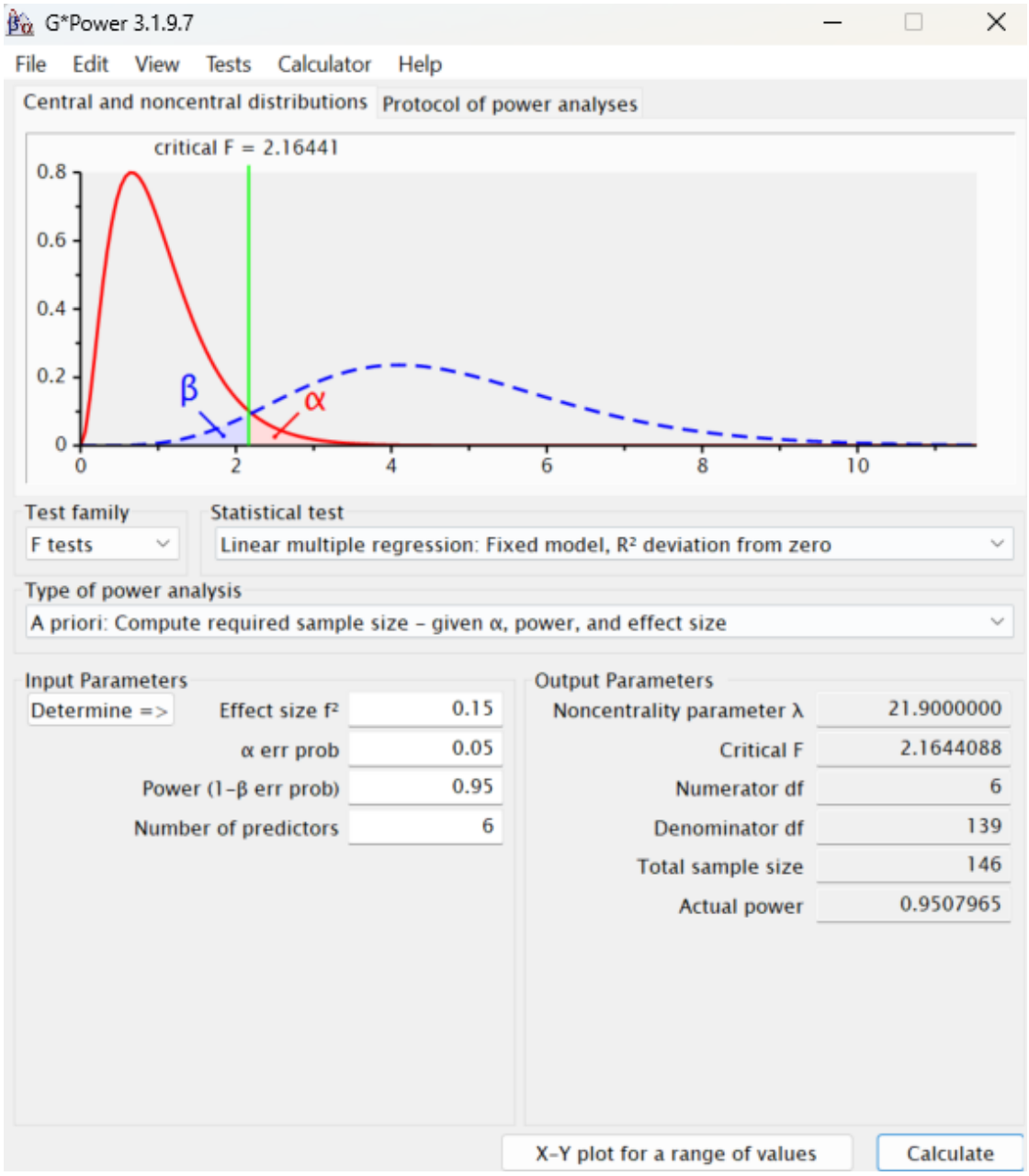
Appendix 9.4: Descriptive Statistics Sample Nationality Distribution

Nationality

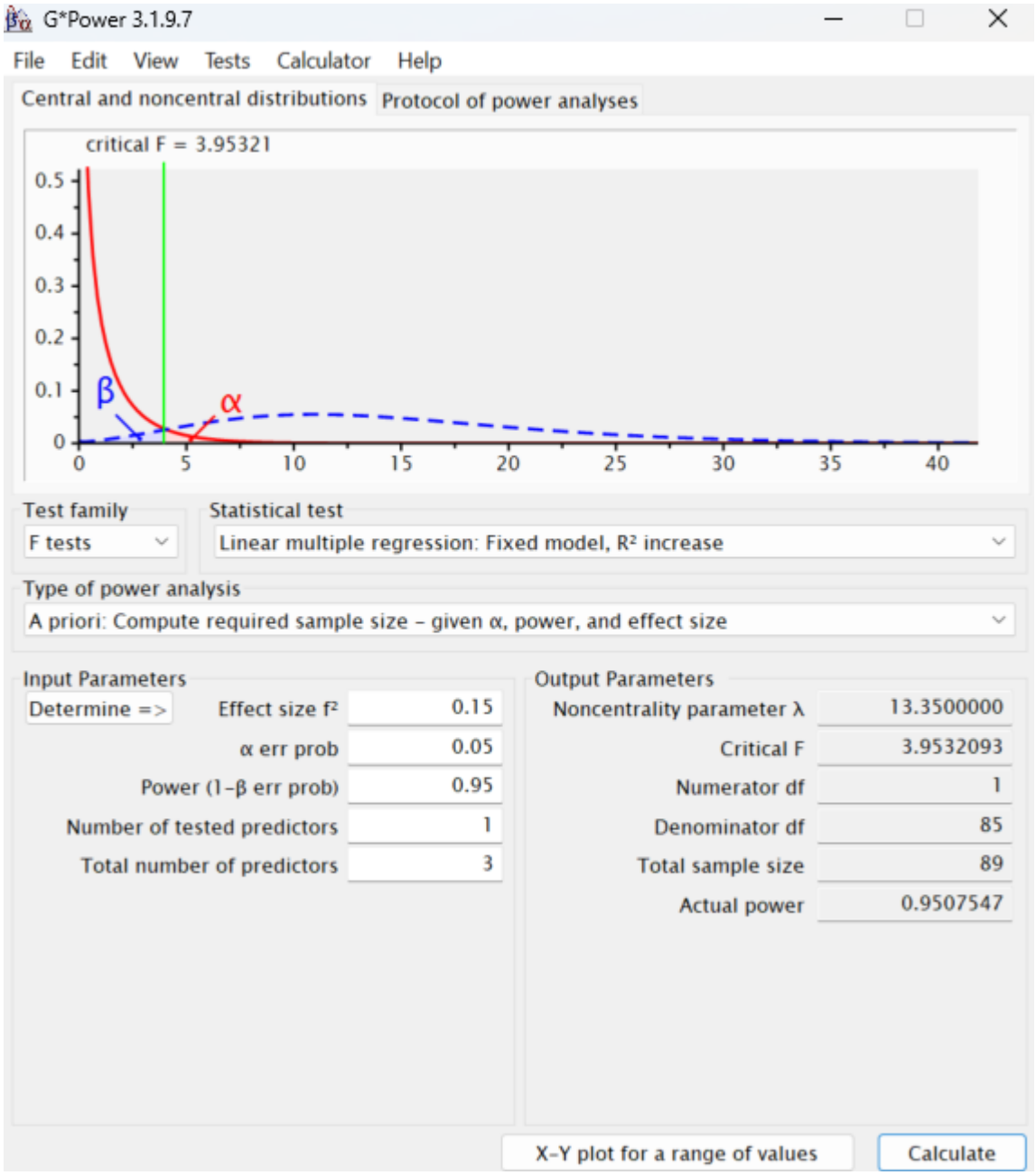
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	American	9	3.9	3.9	3.9
	Austrian	2	.9	.9	4.7
	Belgian	1	.4	.4	5.2
	Brazilian	2	.9	.9	6.0
	British	3	1.3	1.3	7.3
	Canadian	1	.4	.4	7.7
	Colombian	1	.4	.4	8.2
	Croatian	1	.4	.4	8.6
	Danish	1	.4	.4	9.0
	Dutch	1	.4	.4	9.4
	Ecuadorian	2	.9	.9	10.3
	Finnish	1	.4	.4	10.7
	French	2	.9	.9	11.6
	German	163	70.0	70.0	81.5
	Irish	13	5.6	5.6	87.1
	Italian	9	3.9	3.9	91.0
	Luxembourgish	1	.4	.4	91.4
	Malaysian	1	.4	.4	91.8
	Mexican	1	.4	.4	92.3
	Multiracial	1	.4	.4	92.7
	Norwegian	1	.4	.4	93.1
	Polish	1	.4	.4	93.6
	Portuguese	8	3.4	3.4	97.0
	Russian	2	.9	.9	97.9
	Sammarinese - Dutch	1	.4	.4	98.3
	Swiss	2	.9	.9	99.1
	Tunisian	1	.4	.4	99.6
	Vietnamese	1	.4	.4	100.0
	Total	233	100.0	100.0	

Appendix 10: G*Power Measurements Hypotheses

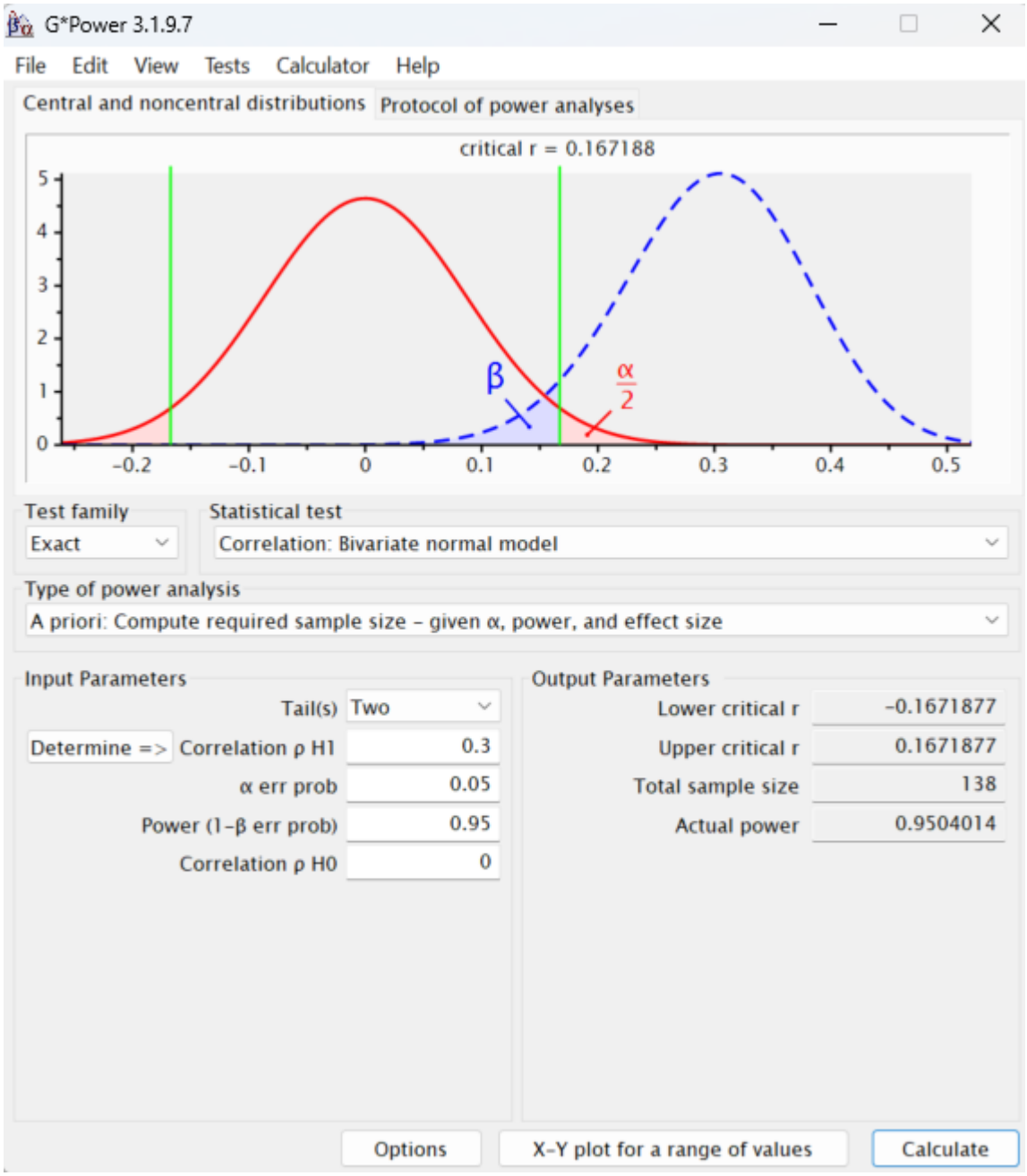
Appendix 10.1: G*Power Measurements Hypothesis 1



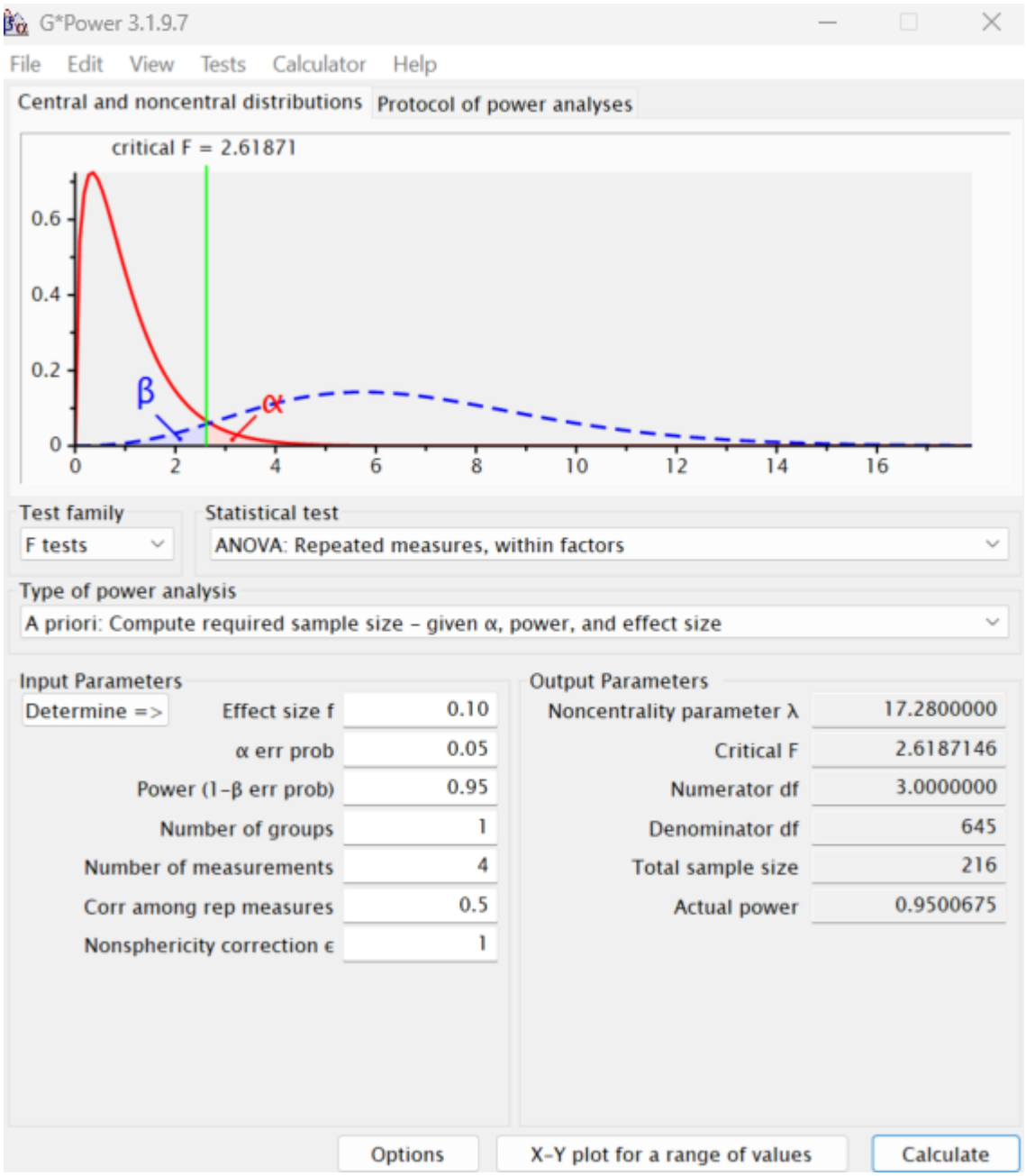
Appendix 10.2: G*Power Measurements Hypothesis 2 and 3



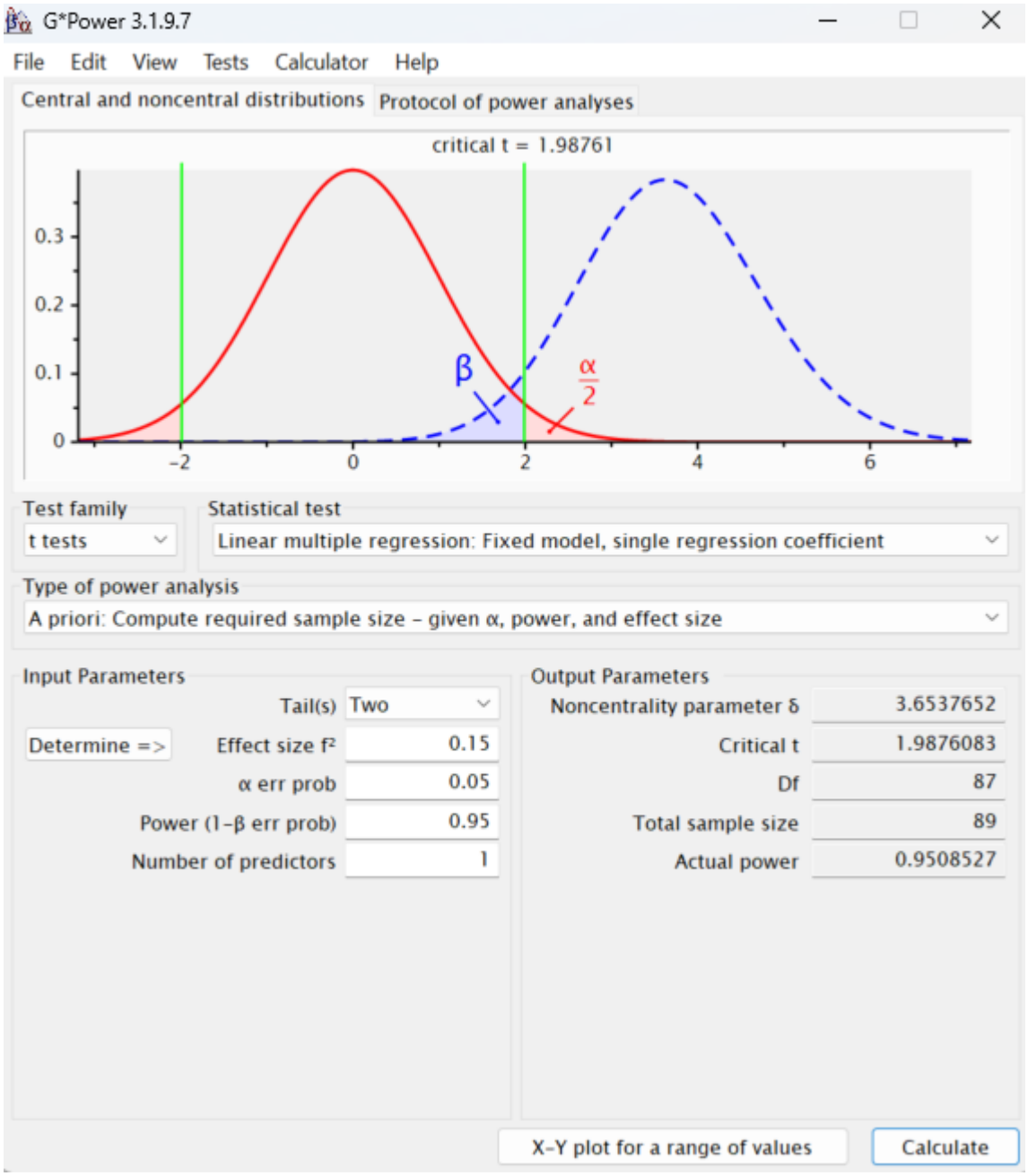
Appendix 10.3: G*Power Measurements Hypothesis 4



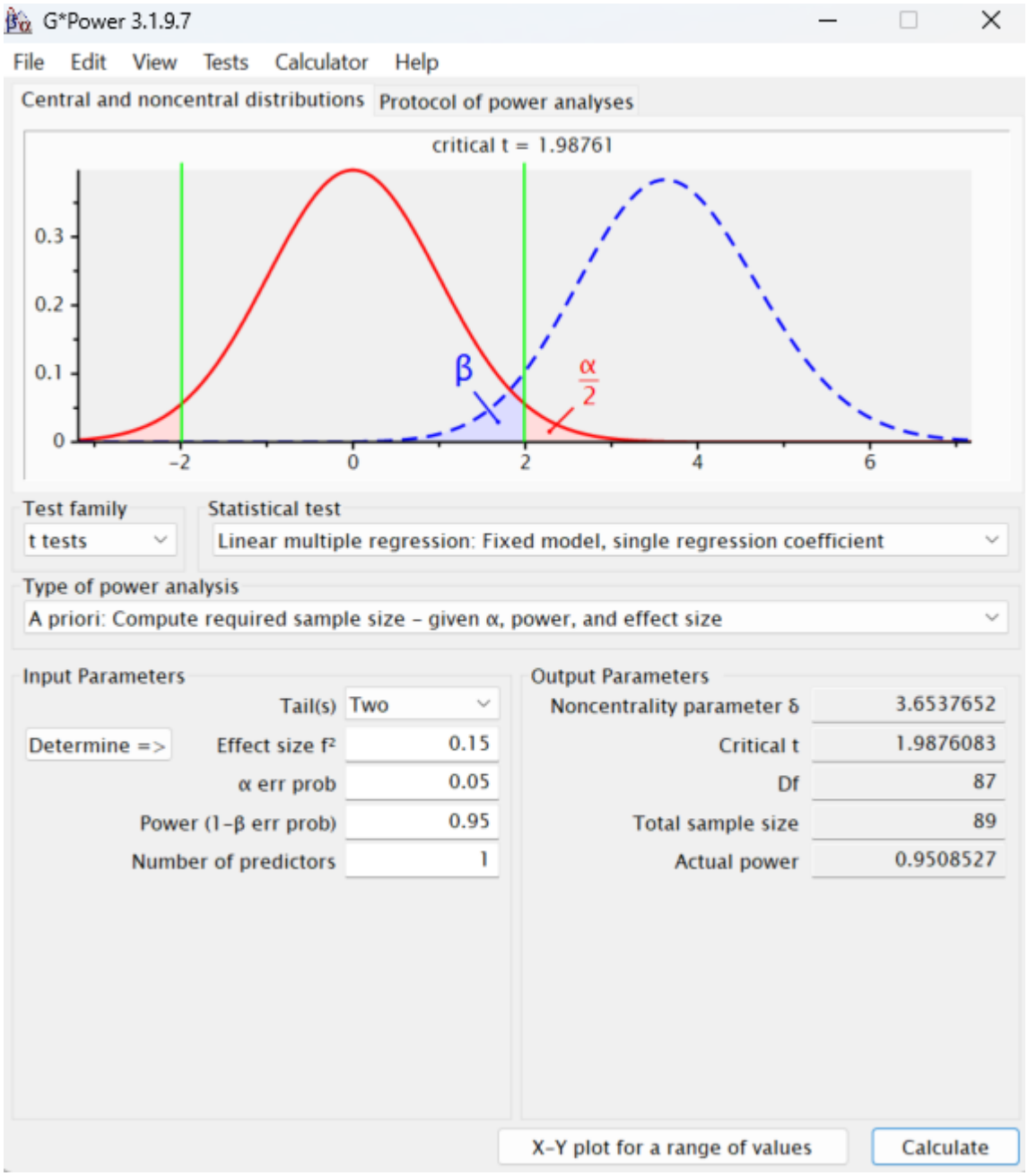
Appendix 10.4: G*Power Measurements Hypothesis 4.1



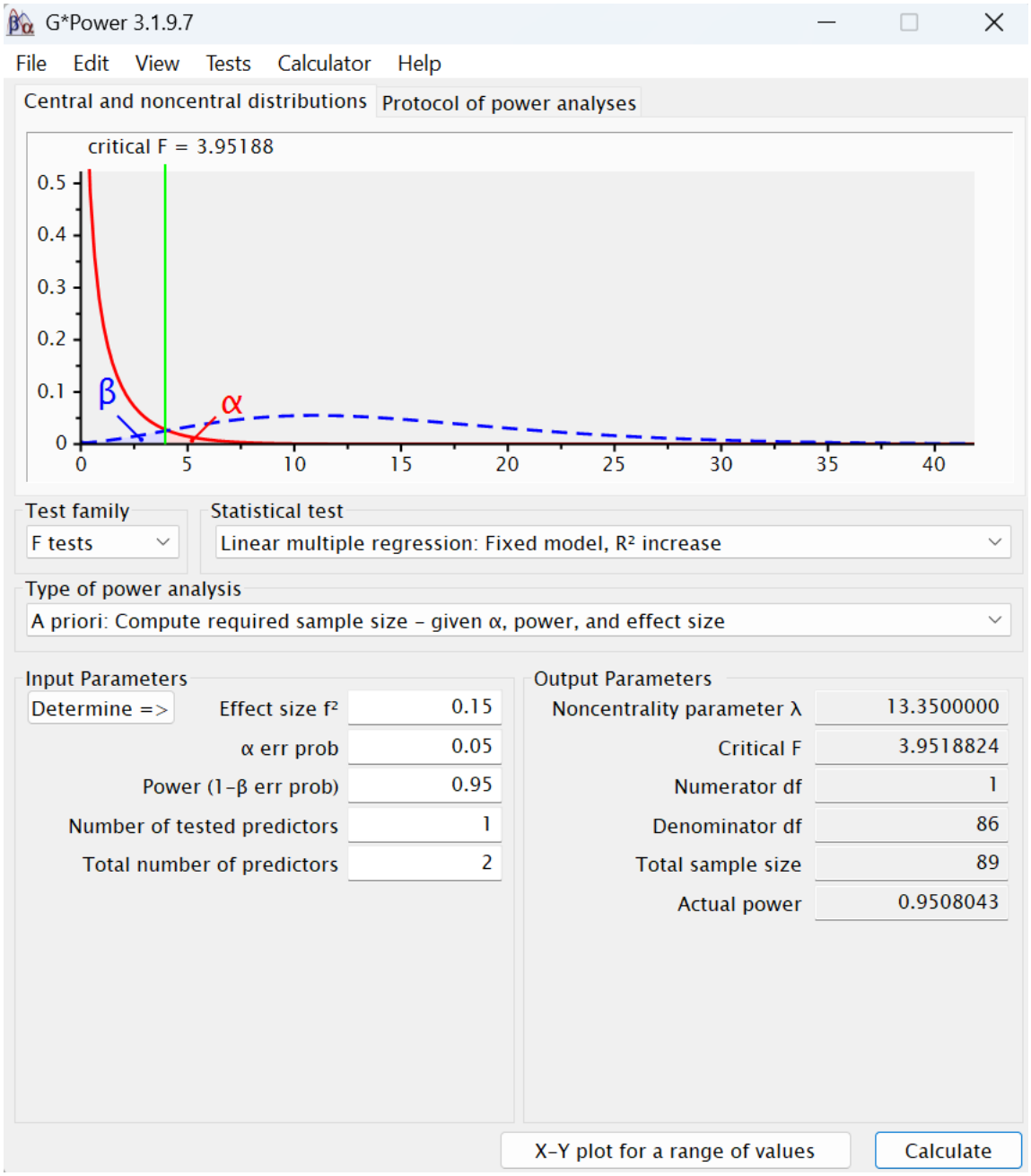
Appendix 10.5: G*Power Measurements Hypothesis 5



Appendix 10.6: G*Power Measurements Hypothesis 5.1 Path a (Age → Effort Expectancy)



Appendix 10.7: G*Power Measurements Hypothesis 5.1 Path b + c' (Age + Effort Expectancy → Usage Frequency)



Appendix 11: Reliability Statistics

Appendix 11.1: Reliability Statistics Performance Expectancy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.905	.905	3

Item Statistics

	Mean	Std. Deviation	N
Q10_PeEx1	4.1159	1.15197	233
Q10_PeEx2	4.2747	1.22548	233
Q10_PeEx3	4.1288	1.21438	233

Inter-Item Correlation Matrix

	Q10_PeEx1	Q10_PeEx2	Q10_PeEx3
Q10_PeEx1	1.000	.799	.723
Q10_PeEx2	.799	1.000	.761
Q10_PeEx3	.723	.761	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q10_PeEx1	8.4034	5.242	.811	.669	.864
Q10_PeEx2	8.2446	4.824	.840	.709	.838
Q10_PeEx3	8.3906	5.084	.783	.616	.887

Appendix 11.2: Reliability Statistics Effort Expectancy

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.863	.863	4

Item Statistics

	Mean	Std. Deviation	N
Q11_EfEx1	4.3820	1.03183	233
Q11_EfEx2	4.2060	1.05477	233
Q11_EfEx3	4.2103	1.01433	233
Q11_EfEx4	4.2532	1.02566	233

Inter-Item Correlation Matrix

	Q11_EfEx1	Q11_EfEx2	Q11_EfEx3	Q11_EfEx4
Q11_EfEx1	1.000	.589	.574	.584
Q11_EfEx2	.589	1.000	.685	.605
Q11_EfEx3	.574	.685	1.000	.632
Q11_EfEx4	.584	.605	.632	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q11_EfEx1	12.6695	7.283	.668	.447	.842
Q11_EfEx2	12.8455	6.898	.732	.548	.816
Q11_EfEx3	12.8412	7.057	.739	.558	.814
Q11_EfEx4	12.7983	7.153	.704	.497	.828

Appendix 11.3: Reliability Statistics Social Influence

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.929	.929	3

Item Statistics

	Mean	Std. Deviation	N
Q12_Soln1	2.9957	1.24047	233
Q12_Soln2	3.1202	1.25711	233
Q12_Soln3	3.1330	1.20858	233

Inter-Item Correlation Matrix

	Q12_Soln1	Q12_Soln2	Q12_Soln3
Q12_Soln1	1.000	.816	.808
Q12_Soln2	.816	1.000	.818
Q12_Soln3	.808	.818	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q12_Soln1	6.2532	5.526	.852	.726	.899
Q12_Soln2	6.1288	5.423	.859	.738	.894
Q12_Soln3	6.1159	5.663	.853	.728	.898

Appendix 11.4: Reliability Statistics Facilitating Conditions

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.740	.747	4

Item Statistics

	Mean	Std. Deviation	N
Q13_FaCo1	4.6052	.99497	233
Q13_FaCo2	4.3863	1.03231	233
Q13_FaCo3	4.2146	1.10108	233
Q13_FaCo4	4.0773	1.14208	233

Inter-Item Correlation Matrix

	Q13_FaCo1	Q13_FaCo2	Q13_FaCo3	Q13_FaCo4
Q13_FaCo1	1.000	.665	.495	.346
Q13_FaCo2	.665	1.000	.477	.249
Q13_FaCo3	.495	.477	1.000	.319
Q13_FaCo4	.346	.249	.319	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q13_FaCo1	12.6781	6.055	.661	.504	.613
Q13_FaCo2	12.8970	6.179	.592	.472	.649
Q13_FaCo3	13.0687	6.099	.546	.307	.674
Q13_FaCo4	13.2060	6.802	.365	.149	.779

Appendix 11.5: Reliability Statistics Hedonic Motivation

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.880	.884	3

Item Statistics

	Mean	Std. Deviation	N
Q14_HeMo1	4.0472	1.01811	233
Q14_HeMo2	4.0901	1.03621	233
Q14_HeMo3	3.6481	1.15060	233

Inter-Item Correlation Matrix

	Q14_HeMo1	Q14_HeMo2	Q14_HeMo3
Q14_HeMo1	1.000	.829	.673
Q14_HeMo2	.829	1.000	.649
Q14_HeMo3	.673	.649	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q14_HeMo1	7.7382	3.944	.823	.719	.784
Q14_HeMo2	7.6953	3.937	.802	.703	.801
Q14_HeMo3	8.1373	3.860	.691	.479	.907

Appendix 11.6: Reliability Statistics Habit

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.835	.841	3

Item Statistics

	Mean	Std. Deviation	N
Q15_Ha1	3.2575	1.42416	233
Q15_Ha2	2.1588	1.18381	233
Q15_Ha3	2.4163	1.34006	233

Inter-Item Correlation Matrix

	Q15_Ha1	Q15_Ha2	Q15_Ha3
Q15_Ha1	1.000	.668	.560
Q15_Ha2	.668	1.000	.684
Q15_Ha3	.560	.684	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q15_Ha1	4.5751	5.366	.666	.467	.808
Q15_Ha2	5.6738	5.962	.765	.586	.717
Q15_Ha3	5.4163	5.684	.674	.487	.793

Appendix 11.7: Reliability Statistics Behavioral Intention

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.897	.898	3

Item Statistics

	Mean	Std. Deviation	N
Q16_BeIn1	4.1888	1.24515	233
Q16_BeIn2	3.3605	1.32567	233
Q16_BeIn3	3.9099	1.23020	233

Inter-Item Correlation Matrix

	Q16_BeIn1	Q16_BeIn2	Q16_BeIn3
Q16_BeIn1	1.000	.692	.791
Q16_BeIn2	.692	1.000	.757
Q16_BeIn3	.791	.757	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Q16_BeIn1	7.2704	5.741	.789	.646	.861
Q16_BeIn2	8.0987	5.486	.766	.597	.883
Q16_BeIn3	7.5494	5.593	.841	.710	.817

Appendix 12: Exploratory Factor Analysis (EFA) with Principal Axis Factoring and Varimax

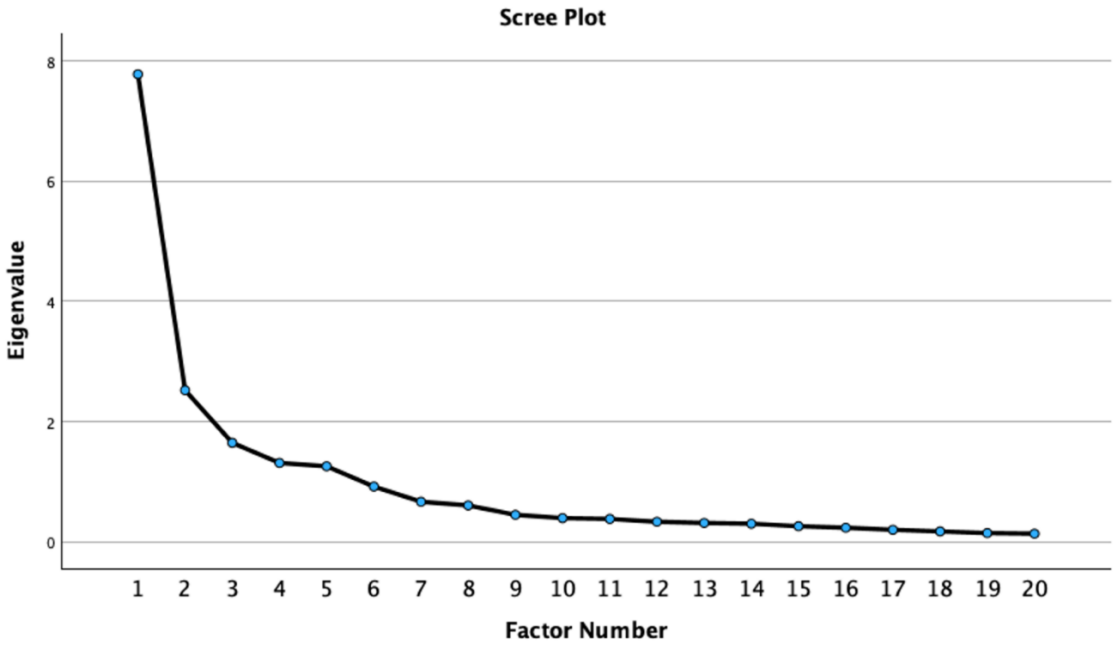
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.883
Bartlett's Test of Sphericity	Approx. Chi-Square	2998.196
	df	190
	Sig.	<.001

Total Variance Explained

	Initial Eigenvalues			Rotation Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.780	38.899	38.899	3.276	16.381	16.381
2	2.521	12.606	51.504	2.939	14.696	31.077
3	1.646	8.232	59.736	2.612	13.060	44.136
4	1.311	6.557	66.293	2.188	10.938	55.074
5	1.255	6.276	72.570	1.736	8.678	63.753
6	.918	4.592	77.161			
7	.665	3.327	80.488			
8	.604	3.018	83.506			
9	.448	2.238	85.743			
10	.392	1.959	87.702			
11	.379	1.895	89.598			
12	.332	1.662	91.260			
13	.311	1.556	92.816			
14	.298	1.492	94.308			
15	.258	1.292	95.600			
16	.233	1.163	96.764			
17	.197	.987	97.750			
18	.171	.857	98.607			
19	.144	.722	99.329			
20	.134	.671	100.000			

Extraction Method: Principal Axis Factoring.



Rotated Factor Matrix[a]

	Factor 1	2	3	4	5
Q10_PeEx1	.443	.641	.305	.119	-.029
Q10_PeEx2	.534	.556	.277	.104	-.032
Q10_PeEx3	.475	.536	.290	.141	-.062
Q11_EfEx1	.664	.105	.102	.128	.205
Q11_EfEx2	.715	.055	.155	.183	.230
Q11_EfEx3	.699	.179	.117	.238	.241
Q11_EfEx4	.628	.063	.082	.241	.218
Q12_Soln1	.149	.265	.852	.075	.067
Q12_Soln2	.125	.271	.824	.141	.139
Q12_Soln3	.196	.216	.835	.145	.123
Q13_FaCo1	.308	.039	.000	.078	.680
Q13_FaCo2	.439	.035	-.069	.142	.663
Q13_FaCo3	.366	.124	.106	.135	.516
Q13_FaCo4	-.028	.059	.203	.000	.474
Q14_HeMo1	.285	.227	.126	.816	.129
Q14_HeMo2	.308	.253	.137	.786	.094
Q14_HeMo3	.136	.168	.089	.699	.059
Q15_Ha1	.199	.693	.255	.231	.204
Q15_Ha2	.008	.745	.149	.195	.155
Q15_Ha3	-.019	.699	.124	.150	.039

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

Appendix 13: Descriptive Statistics and Correlations

Appendix 13.1: Descriptive Statistics and Correlations UTAUT2 Variables

Descriptive Statistics UTAUT2 Variables

	N Statistic	Range Statistic	Minimum Statistic	Maximum Statistic	Mean Statistic	Std. Deviation Statistic	Variance Statistic	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
PeEx_To	233	5.00	1.00	6.00	4.1731	1.09775	1.205	-.848	.159	.444	.318
EfEx_To	233	4.50	1.50	6.00	4.2629	.86841	.754	-.974	.159	1.190	.318
Soln_To	233	5.00	1.00	6.00	3.0830	1.15627	1.337	.090	.159	-.634	.318
FaCo_To	233	5.00	1.00	6.00	4.3208	.80162	.643	-.710	.159	1.179	.318
HeMo_To	233	5.00	1.00	6.00	3.9285	.96074	.923	-.448	.159	.313	.318
Ha_To	233	5.00	1.00	6.00	2.6109	1.14438	1.310	.636	.159	.199	.318
BeIn_To	233	5.00	1.00	6.00	3.8197	1.15467	1.333	-.555	.159	.111	.318
Valid N (listwise)	233										

Correlations UTAUT2 Variables

		PeEx_To	EfEx_To	Soln_To	FaCo_To	HeMo_To	Ha_To	BeIn_To
PeEx_To	Pearson Correlation	1	.503**	.541**	.285**	.457**	.587**	.742**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001
	N	233	233	233	233	233	233	233
EfEx_To	Pearson Correlation	.503**	1	.357**	.511**	.472**	.325**	.448**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001
	N	233	233	233	233	233	233	233
Soln_To	Pearson Correlation	.541**	.357**	1	.259**	.343**	.472**	.481**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001
	N	233	233	233	233	233	233	233
FaCo_To	Pearson Correlation	.285**	.511**	.259**	1	.313**	.233**	.343**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001
	N	233	233	233	233	233	233	233
HeMo_To	Pearson Correlation	.457**	.472**	.343**	.313**	1	.433**	.561**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001
	N	233	233	233	233	233	233	233
Ha_To	Pearson Correlation	.587**	.325**	.472**	.233**	.433**	1	.705**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001
	N	233	233	233	233	233	233	233
BeIn_To	Pearson Correlation	.742**	.448**	.481**	.343**	.561**	.705**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	
	N	233	233	233	233	233	233	233

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

Appendix 13.2: Descriptive Statistics and Correlations CDJ Phases

Descriptive Statistics CDJ Phases

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Q6InCoPh	233	5.00	1.00	6.00	2.8283	1.26820	1.608	.378	.159	-.653	.318
Q7AcEvPh	233	5.00	1.00	6.00	3.0258	1.27280	1.620	.116	.159	-.820	.318
Q8ClPh	233	5.00	1.00	6.00	2.2876	1.23828	1.533	.826	.159	-.040	.318
Q9PoExPh	233	4.00	1.00	5.00	2.3605	1.18488	1.404	.635	.159	-.454	.318
CDJ_To	233	4.50	1.00	5.50	2.6255	.97962	.960	.366	.159	-.354	.318
Valid N (listwise)	233										

Correlations CDJ Phases

		Q6InCoPh	Q7AcEvPh	Q8ClPh	Q9PoExPh	CDJ_To
Q6InCoPh	Pearson Correlation	1	.630**	.457**	.417**	.799**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	N	233	233	233	233	233
Q7AcEvPh	Pearson Correlation	.630**	1	.589**	.417**	.841**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	N	233	233	233	233	233
Q8ClPh	Pearson Correlation	.457**	.589**	1	.461**	.794**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001
	N	233	233	233	233	233
Q9PoExPh	Pearson Correlation	.417**	.417**	.461**	1	.718**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	N	233	233	233	233	233
CDJ_To	Pearson Correlation	.799**	.841**	.794**	.718**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	233	233	233	233	233

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

Appendix 14: H1 Model Summary Multiple Regression UTAUT2 Variables

Model Summary[b]

					Change Statistics			
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.836[a]	.699	.691	.64189	.699	87.453	6	226	<.001

a. Predictors: (Constant), Ha_To, FaCo_To, HeMo_To, Soln_To, EfEx_To, PeEx_To

b. Dependent Variable: BeIn_To

Appendix 15: H1 Beta Coefficients and VIF Multiple Regression UTAUT2 Variables

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-.346	.268		-1.287	.199		
	PeEx_To	.453	.055	.431	8.242	<.001	.487	2.052
	EfEx_To	-.025	.065	-.019	-.383	.702	.559	1.790
	Soln_To	-.002	.045	-.002	-.045	.964	.658	1.520
	FaCo_To	.125	.062	.087	2.028	.044	.726	1.378
	HeMo_To	.231	.054	.192	4.315	<.001	.671	1.489
	Ha_To	.359	.048	.356	7.512	<.001	.593	1.686

a. Dependent Variable: BeIn_To

Appendix 16: H2 Moderation Analysis for Sex on Social Influence Toward Behavioral Intention

```
**************************************************************************
OUTCOME VARIABLE:
 BeIn_To

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4823      .2326     1.0365    23.1425     3.0000   229.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8239      .0958    39.9074      .0000     3.6351     4.0127
SoIn_To       .5196      .0831     6.2503      .0000      .3558      .6834
Sex          -.0055      .1335     -.0412      .9672     -.2686      .2576
Int_1        -.0763      .1157     -.6597      .5101     -.3044      .1517

Product terms key:
 Int_1    :        SoIn_To  x        Sex

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0015      .4352     1.0000   229.0000      .5101
----------
    Focal predict: SoIn_To  (X)
          Mod var: Sex      (W)

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   SoIn_To    Sex        BeIn_To    .
BEGIN DATA.
    -1.0830      .0000     3.2612
     -.0830      .0000     3.7808
     1.2504      .0000     4.4736
    -1.0830     1.0000     3.3383
     -.0830     1.0000     3.7816
     1.2504     1.0000     4.3726
END DATA.
GRAPH/SCATTERPLOT=
 SoIn_To  WITH     BeIn_To  BY       Sex      .
```

Appendix 17: H3 Moderation Analysis for Age on Hedonic Motivation Toward Behavioral Intention

```
**************************************************************************
OUTCOME VARIABLE:
 BeIn_To

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5769      .3328      .9013    38.0696     3.0000   229.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8811      .0669    58.0168      .0000     3.7493     4.0129
HeMo_To       .6577      .0700     9.3976      .0000      .5198      .7956
Age           .0126      .0085     1.4776      .1409     -.0042      .0294
Int_1         .0161      .0065     2.4892      .0135      .0034      .0288

Product terms key:
 Int_1    :        HeMo_To  x        Age

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0181     6.1960     1.0000   229.0000      .0135
----------
    Focal predict: HeMo_To  (X)
          Mod var: Age      (W)

Conditional effects of the focal predictor at values of the moderator(s):

        Age     Effect         se          t          p       LLCI       ULCI
    -6.3797      .5549      .0831     6.6803      .0000      .3913      .7186
    -3.8197      .5962      .0754     7.9049      .0000      .4476      .7448
     4.1803      .7250      .0737     9.8363      .0000      .5798      .8702
```

```
There are no statistical significance transition points within the observed
range of the moderator found using the Johnson-Neyman method.

Conditional effect of focal predictor at values of the moderator:
        Age     Effect         se          t          p       LLCI       ULCI
   -12.8197      .4512      .1113     4.0558      .0001      .2320      .6705
   -10.2007      .4934      .0986     5.0017      .0000      .2990      .6878
    -7.5816      .5356      .0875     6.1197      .0000      .3631      .7080
    -4.9626      .5778      .0785     7.3605      .0000      .4231      .7324
    -2.3436      .6199      .0724     8.5660      .0000      .4773      .7625
      .2755      .6621      .0699     9.4704      .0000      .5244      .7999
     2.8945      .7043      .0715     9.8501      .0000      .5634      .8452
     5.5136      .7465      .0769     9.7092      .0000      .5950      .8979
     8.1326      .7886      .0853     9.2407      .0000      .6205      .9568
    10.7517      .8308      .0961     8.6476      .0000      .6415     1.0201
    13.3707      .8730      .1084     8.0531      .0000      .6594     1.0866
    15.9898      .9152      .1218     7.5108      .0000      .6751     1.1552
    18.6088      .9573      .1361     7.0355      .0000      .6892     1.2254
    21.2279      .9995      .1509     6.6254      .0000      .7023     1.2968
    23.8469     1.0417      .1661     6.2729      .0000      .7145     1.3689
    26.4660     1.0839      .1816     5.9693      .0000      .7261     1.4416
    29.0850     1.1260      .1973     5.7067      .0000      .7372     1.5148
    31.7041     1.1682      .2132     5.4782      .0000      .7480     1.5884
    34.3231     1.2104      .2293     5.2781      .0000      .7585     1.6622
    36.9422     1.2526      .2455     5.1018      .0000      .7688     1.7363
    39.5612     1.2947      .2618     4.9455      .0000      .7789     1.8106
    42.1803     1.3369      .2782     4.8062      .0000      .7888     1.8850

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   HeMo_To    Age        BeIn_To    .
BEGIN DATA.
     -.9285    -6.3797     3.2855
      .0715    -6.3797     3.8405
     1.0715    -6.3797     4.3954
     -.9285    -3.8197     3.2795
      .0715    -3.8197     3.8756
     1.0715    -3.8197     4.4718
     -.9285     4.1803     3.2605
      .0715     4.1803     3.9855
     1.0715     4.1803     4.7105
END DATA.
GRAPH/SCATTERPLOT=
 HeMo_To  WITH     BeIn_To  BY       Age      .
```

Appendix 18: H4 Pearson Correlation Behavioral Intention and Overall CDJ Usage Frequency

Correlations

		BeIn_To	CDJ_To
BeIn_To	Pearson Correlation	1	.611**
	Sig. (2-tailed)		<.001
	N	233	233
CDJ_To	Pearson Correlation	.611**	1
	Sig. (2-tailed)	<.001	
	N	233	233

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

Appendix 19: H4.1 ANOVA Differences in AI Usage Frequency Across Entire CDJ

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
CDJ_Phase	Pillai's Trace	.322	36.466[b]	3.000	230.000	<.001	.322
	Wilks' Lambda	.678	36.466[b]	3.000	230.000	<.001	.322
	Hotelling's Trace	.476	36.466[b]	3.000	230.000	<.001	.322
	Roy's Largest Root	.476	36.466[b]	3.000	230.000	<.001	.322

a. Design: Intercept
Within Subjects Design: CDJ_Phase

b. Exact statistic

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Epsilon[b] Huynh-Feldt	Epsilon[b] Lower-bound
CDJ_Phase	.906	22.724	5	<.001	.944	.957	.333

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept
Within Subjects Design: CDJ_Phase

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
CDJ_Phase	Sphericity Assumed	89.883	3	29.961	38.626	<.001	.143
	Greenhouse-Geisser	89.883	2.832	31.741	38.626	<.001	.143
	Huynh-Feldt	89.883	2.870	31.314	38.626	<.001	.143
	Lower-bound	89.883	1.000	89.883	38.626	<.001	.143
Error(CDJ_Phase)	Sphericity Assumed	539.867	696	.776			
	Greenhouse-Geisser	539.867	656.960	.822			
	Huynh-Feldt	539.867	665.919	.811			
	Lower-bound	539.867	232.000	2.327			

Appendix 20: H4.1 ANOVA Pairwise Comparison CDJ Phases

Pairwise Comparisons

Measure: MEASURE_1

(I) CDJ_Phase	(J) CDJ_Phase	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	95% Confidence Interval for Difference[b] Upper Bound
1	2	-.197*	.072	.038	-.388	-.007
	3	.541*	.086	<.001	.313	.768
	4	.468*	.087	<.001	.237	.699
2	1	.197*	.072	.038	.007	.388
	3	.738*	.075	<.001	.540	.937
	4	.665*	.087	<.001	.434	.897
3	1	-.541*	.086	<.001	-.768	-.313
	2	-.738*	.075	<.001	-.937	-.540
	4	-.073	.082	1.000	-.292	.147
4	1	-.468*	.087	<.001	-.699	-.237
	2	-.665*	.087	<.001	-.897	-.434
	3	.073	.082	1.000	-.147	.292

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Appendix 21: H4.1 ANOVA Mean Values Usage Frequency CDJ Phases

Estimates

Measure: MEASURE_1

CDJ_Phase	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
1	2.828	.083	2.665	2.992
2	3.026	.083	2.861	3.190
3	2.288	.081	2.128	2.447
4	2.361	.078	2.208	2.513

Appendix 22: H5 Simple Linear Regression Analysis of Age on Overall AI Usage Frequency Across All Phases of CDJ

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.073[a]	.005	.001	.97910	.005	1.247	1	231	.265

a. Predictors: (Constant), Age

b. Dependent Variable: CDJ_To

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.826	.190		14.852	<.001		
	Age	-.007	.006	-.073	-1.117	.265	1.000	1.000

a. Dependent Variable: CDJ_To

Appendix 23: H5.1 Mediation Analysis of Effort Expectancy Regarding Age and AI Usage Frequency in the Active Evaluation Phase

```
**************************************************************************
OUTCOME VARIABLE:
 EfEx_To

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3459      .1197      .6668    31.4048     1.0000   231.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.0999      .1587    32.1442      .0000     4.7873     5.4125
Age          -.0281      .0050    -5.6040      .0000     -.0379     -.0182

**************************************************************************
OUTCOME VARIABLE:
 Q7AcEvPh

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3564      .1270     1.4265    16.7339     2.0000   230.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      .5444      .5429     1.0027      .3171     -.5254     1.6141
Age           .0057      .0078      .7262      .4684     -.0097      .0211
EfEx_To       .5424      .0962     5.6362      .0000      .3528      .7320


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0057      .0078      .7262      .4684     -.0097      .0211

Indirect effect(s) of X on Y:
            Effect     BootSE   BootLLCI   BootULCI
EfEx_To     -.0152      .0045     -.0249     -.0074

************************ ANALYSIS NOTES AND ERRORS ************************
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