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**Project Submission Sheet**

**Student Name:** Shreyashi Pal

**Student ID:** X22238212

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**Lecturer:** Fabián Armendáriz

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# AI Acknowledgement Supplement

## Dissertation

## Artificial Intelligence Technology Acceptance: A survey based perception study using UTAUT

Your Name/Student Number	Course	Date
Shreyashi Pal/ X22238212	MSc in Management	10.08.2024

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click [here](#).

## AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
ChatGPT.com	Used as a guidance tool, or to bounce ideas and gather information to assist understanding and meaning	<a href="https://chatgpt.com">https://chatgpt.com</a>

## Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses

received, and how these responses were utilized or modified in the assignment. **One table should be used for each tool used.**

ChatGPT	
Used as a guidance tool, or to bounce ideas and gather information to assist understanding and meaning of terminologies and theories	
What is CFA in quantitative research?	<p>In quantitative research, CFA stands for Confirmatory Factor Analysis. It is a statistical technique used to test the hypothesis that the relationships between observed variables and their underlying latent constructs (factors) are consistent with the researcher's expectations. CFA is often employed in social sciences, psychology, and other fields to validate the factor structure of a set of observed variables.</p> <p>Key aspects of CFA include:</p> <ol style="list-style-type: none"> <li>1. <b>Hypothesis Testing</b>: CFA is used to confirm or reject the hypothesized factor structure. The researcher specifies the number of factors and the relationships between factors and observed variables based on theoretical considerations or previous research.</li> <li>2. <b>Model Specification</b>: The researcher defines a model, including the number of factors and which observed variables are associated with which factors. This model is then tested against the actual data.</li> </ol>

3. **Measurement Model**: CFA focuses on the measurement model, which describes how measured variables represent latent constructs. It helps in assessing the validity and reliability of the constructs.

4. **Goodness-of-Fit**: Various statistical indices are used to assess how well the specified model fits the observed data. Commonly used indices include the Chi-square test, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI).

5. **Parameter Estimation**: CFA estimates factor loadings (the strength of the relationship between observed variables and their corresponding factors), error variances, and sometimes covariances between factors.

6. **Applications**: It is widely used in the development and validation of psychological tests, surveys, and questionnaires. It helps in ensuring that the measures are accurately capturing the intended constructs.

In summary, CFA is a powerful tool for validating the structure of a set of observed variables in relation to their underlying latent factors, based on predefined hypotheses.

<p>Can you help me understand what's a latent factor?</p>	<p>A latent factor, also known as a latent variable or construct, is an unobserved variable that is inferred from observed variables within a dataset. Latent factors represent underlying, abstract concepts that cannot be directly measured but are estimated through multiple observed indicators (variables).</p> <p>### Key Characteristics of Latent Factors:</p> <ol style="list-style-type: none"> <li>1. <b>Abstract Nature</b>: Latent factors are theoretical constructs, such as intelligence, satisfaction, or anxiety, that cannot be directly observed or measured.</li> <li>2. <b>Multiple Indicators</b>: They are inferred from multiple observed variables that are believed to be influenced by the latent factor. For example, a latent factor like "math ability" might be inferred from various test scores in different areas of mathematics.</li> <li>3. <b>Dimensionality Reduction</b>: Latent factors help to simplify complex data by reducing the number of observed variables into a smaller number of underlying dimensions. This makes it easier to understand and analyze the data.</li> <li>4. <b>Model Specification</b>: In techniques like Confirmatory Factor Analysis (CFA),</li> </ol>
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researchers specify models that define the relationships between latent factors and observed variables. The goal is to see if the observed data fits the theoretical model.

### ### Example of Latent Factors:

Consider a psychological construct like "depression." Depression cannot be measured directly, but several observable indicators (like questionnaire responses) can provide information about it. Indicators might include:

- Frequency of feeling sad
- Changes in appetite
- Sleep disturbances
- Lack of interest in activities

These observed variables are used to infer the presence and severity of the latent factor "depression."

### ### Usage in Research:

- **\*\*Confirmatory Factor Analysis (CFA)\*\***: Used to test if the data fits a hypothesized measurement model involving latent factors.
- **\*\*Exploratory Factor Analysis (EFA)\*\***: Used to identify potential latent factors without predefined hypotheses.

	<p>- <b>**Structural Equation Modeling (SEM)**</b>: Integrates latent factor analysis with regression modeling to examine complex relationships between observed and latent variables.</p> <p>### Visualization:</p> <p>In a factor analysis model, you might see latent factors represented as circles or ovals, while observed variables are represented as squares or rectangles. Arrows indicate the direction of influence from latent factors to observed variables.</p> <p>### Importance:</p> <p>Latent factors are crucial for understanding underlying dimensions in data that are not directly measurable. They provide a means to study abstract concepts rigorously and quantitatively, enhancing the validity and reliability of research findings in fields like psychology, education, and social sciences.</p>
Can I do it using SPSS?	<p>Yes, you can perform Confirmatory Factor Analysis (CFA) using SPSS, specifically through the AMOS (Analysis of Moment Structures) module, which is designed for structural equation modeling (SEM). Here is a general overview of how you can conduct CFA in SPSS using AMOS:</p>



### ### Steps to Perform CFA in SPSS with AMOS

1. **\*\*Install AMOS\*\***: Ensure you have the AMOS module installed. It is an add-on package for SPSS.

2. **\*\*Prepare Your Data\*\***:

- Make sure your data is clean and properly formatted.

- Identify the observed variables (indicators) and the latent factors they are supposed to measure.

3. **\*\*Open AMOS\*\***:

- Launch AMOS Graphics from the SPSS interface.

4. **\*\*Specify the Model\*\***:

- Use the drawing tools to create your measurement model. Draw circles (latent factors) and squares (observed variables).

- Draw arrows from latent factors to their corresponding observed variables, indicating which observed variables are associated with which latent factors.

5. **\*\*Set Parameters\*\***:

- Specify the paths (factor loadings), error terms, and any covariances or correlations between factors if applicable.

6. **\*\*Define the Model\*\***:

- In the "Data" menu, select "Data Files" to load your dataset.

- In the "Analyze" menu, specify the estimation method and other options as needed (usually Maximum Likelihood Estimation is used).

7. **\*\*Run the Analysis\*\***:

- Click on the "Calculate Estimates" button to run the CFA.

- AMOS will provide output including model fit indices, factor loadings, error variances, and modification indices.

8. **\*\*Evaluate the Model\*\***:

- Check the goodness-of-fit indices to assess how well the model fits the data. Common indices include Chi-square, RMSEA, CFI, and TLI.

- Evaluate the factor loadings to see if the observed variables load significantly onto the latent factors as expected.

9. **\*\*Modify the Model\*\*** (if needed):

- If the initial model does not fit well, you can use modification indices to make adjustments, such as adding or removing paths.

### Example:

Assume you have a dataset with observed variables related to two latent factors: "Anxiety" and "Depression." Your observed variables might include items from a questionnaire like feeling nervous, sleep disturbances, lack of interest, etc.

1. **\*\*Draw the Model\*\***: Create two circles labeled "Anxiety" and "Depression" and connect them to their corresponding observed variables.

2. **\*\*Specify Relationships\*\***: Draw arrows from "Anxiety" to items like "feeling nervous" and "sleep disturbances." Draw arrows from "Depression" to items like "lack of interest" and "changes in appetite."

3. **\*\*Estimate and Evaluate\*\***: Run the analysis, check the factor loadings, and evaluate the fit indices.

### Tips:

- **\*\*Goodness-of-Fit Indices\*\***: Aim for values indicating a good fit, such as RMSEA < 0.08, CFI > 0.90, and TLI > 0.90.

- **\*\*Factor Loadings\*\***: Significant factor loadings (e.g., standardized loadings > 0.5) indicate that the observed variables are good indicators of the latent factors.

### Resources:

	<ul style="list-style-type: none"> <li>- <b>**AMOS User Guide**</b>: The official documentation provides detailed instructions and examples.</li> <li>- <b>**Online Tutorials**</b>: There are many tutorials available online (videos, articles) that can guide you through the process step-by-step.</li> </ul> <p>Performing CFA using SPSS and AMOS can be a powerful way to validate your measurement models and ensure the reliability and validity of your constructs.</p>

## Evidence of AI Usage

This section includes evidence of significant prompts and responses used or generated through the AI tool. It should provide a clear understanding of the extent to which the AI tool was used in the assignment. Evidence may be attached via screenshots or text.

## Additional Evidence:

None of the actual content written in the dissertation has been sourced through AI. AI tool (ChatGPT) has only been used to clarify areas of confusion, specifically for the data analysis methods using SPSS.

# Artificial Intelligence Technology Acceptance: A survey based perception study using UTAUT

Shreyashi Pal

MSc in Management (2023-24)

National College of Ireland

Dissertation submitted to the National College of Ireland August, 2024

# Abstract

Artificial intelligence (AI) technology is garnering a lot of attention from academics as well as businesses. The use of AI is increasing within business management, whilst it continues to be an important topic of discussion within the tech world. While a lot has been researched around the advantages and disadvantages of using AI, and the challenges that AI technology adoption brings, current literature is scarce when it comes to people's attitude around AI technology, is it being accepted by professionals or not? Technology adoption models and theories have been researched for decades now, since for any technology to be successful, it must be accepted and used by people. This study aims at evaluating the overall attitude, of professionals working within Ireland, while further finding the factors that impact this perception, and presents a model grounded in the UTAUT (Unified theory of acceptance and use of technology). The descriptive research uses a quantitative method of research, gathering primary data through an online survey, replicating a questionnaire from a global study with similar research intent. The results show overall positive attitude towards AI technology acceptance, in line with the global study, while a strong correlation was identified between UTAUT constructs Performance expectancy, Effort expectancy, Social Influence, Facilitating Conditions, and proved that "trust" is a significant factor that impacts the behavioural intention and actual use behaviour, while the data analysis showed the moderators, Age and Gender, did not have a significant impact on the attitude, but income level impacted the construct "Trust", among the Irish professionals, participants in the survey. A simplified model was proposed based on the hypotheses testing, correlation testing, factor analysis, linear regressions, and cross-tabulation, where these factors, constructs, and moderators were brought together.

## Declaration

## Submission of Thesis and Dissertation

**National College of Ireland**  
**Research Students Declaration Form**  
*(Thesis/Author Declaration Form)*

**Name:** Shreyashi Pal





**Student Number: X22238212**

**Degree for which thesis is submitted: MSc in Management**

**Title of Thesis: Artificial Intelligence Technology Acceptance: A survey based perception study using UTAUT**

**Date: 10.08.2024**

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- 
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## Acknowledgement

I would sincerely like to express my gratitude to the people who participated in the survey of this research, without whom this study would not have been possible. My supervisor, Fabián Armendáriz, for his guidance and support throughout the process of this study, providing clarity and direction every time I was astray. I would also like to thank the NCI academic support team, for their kindness towards me and offering me the support during a tough time, and the library team at NCI who have helped me multiple times by offering me feedback on the writing.

On a personal level, I wish to acknowledge and thank my family, friends, and colleagues, who have constantly supported me, through thick and thin, fed me, and cared for me, giving me the space and encouragement to be able to achieve the task, I thank you all.



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## List of Abbreviations

1. What is your age? (Age\_N)
2. What is your gender? (Gender\_N)
3. What is your highest education level? (Education\_N)
4. What is your income level? (Income\_N)
5. AI can increase efficiency and accuracy in tasks. (FlunAccu)
6. AI can offer convenience and save time. (Convnsavetime )
7. AI can improve decision-making processes (DecMake)
8. AI can help solve complex problems. (CompProb)
9. AI can lead to cost savings (CostSav)
10. AI can create new job opportunities. (NJobO)
11. AI may lead to job displacement. (JobDis)
12. AI may violate privacy concerns (AIPriv)
13. AI may be used for malicious purposes. (MalPurp)
14. AI may cause errors and mistakes. (Err)
15. AI may perpetuate bias and discrimination. (Bias)
16. AI may have unintended consequences. (UnintCons)
17. I trust AI to perform tasks accurately. (TAccu)
18. I trust AI to make reliable decisions. (TRelDeci)
19. I believe AI is predictable. (Tprecit)
20. I have confidence in AI's ability to learn. (TLearn)
21. I trust AI to keep my personal data secure. (TDataSec)
22. I trust AI to be used ethically. (Tethic)
23. I trust an AI has less or no personal interests compared to humans. (NoPers)
24. The government does not solve important issues like climate change.  
(GovClimChng)
25. AI can help address societal issues such as climate change and social  
inequality. (AISocClimChng)
26. Governments cannot solve global issues. (GovGbls)
27. AI has the potential to solve global issues (AIGlobls)
28. Politicians and countries have too many vested interests. (PInvest)
29. AI has the potential to make society more equitable. (Alequit)

30. AI can help create solutions to societal issues. (AISoclss)
31. I use AI-powered products and services frequently. (AIProdUse)
32. I have a basic understanding of what AI is and how it works. (AI\_B\_Und)
33. I have no experience with AI. (No\_AI)
34. I am comfortable using AI-powered products and services. (ComfAI)
35. I have encountered issues with AI-powered products and services in the past.  
(Iss\_AIprod)
36. My cultural background influences my attitudes towards AI. (CAttAI)
37. Different cultures may have different perceptions of AI. (CDif)
38. AI development should take cultural differences into account. (CdifCons)
39. My cultural beliefs impact my level of trust in AI. (CTrstAI)
40. Cultural diversity can bring unique perspectives to the development and use  
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41. I believe AI is the future for human kind. (AlfutMK)
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# 1. Introduction

Artificial intelligence (AI) is one of the most trending topics of research at the moment, not only from the technological perspective but there's an increased attention from a business management perspective towards AI (Raisch, Krakowski, 2021; Li, Bitterly, 2024; Sharma, Kumar, 2024). AI is intrinsically changing the way the world has been operating. While there are benefits such as higher data accuracy, lower rate of errors, lack of personnel dependency and increase in overall efficiency and effectiveness of businesses around the world (Oyekunle, Boohene, 2024; Jorzik, et al, 2024), giving businesses a competitive edge, the fear around AI taking over jobs cannot and should not be neglected.

The adoption of AI technology is beneficial in many ways for businesses around the world, however, the impact of cultural, social, environmental, and political factors vary across the globe and therefore can impact the successful adoption of the AI technology. Raisch and Krakowski (2021) present the lack of focus, in the last 2 decades, in the research around AI from a management perspective and highlights the importance of studying societal implications of AI technology. This is further explored by Li and Bitterly (2024) from the point of view of how the lack of benevolence impacts employee trust within AI technology and therefore emphasise the importance of understanding other factors affecting the employee or human motivations within an organisation. The challenges around AI have been discussed in terms of data security, transparency, ethicality, and algorithmic bias (Jankovic, Curovic, 2023), lacking research with primary data based on public perspective. For new technology to be adopted within organisations, change management practices are crucial in maintaining trust and a successful adoption to reap the benefits of AI. The republic of Ireland has many technology companies' headquarters, such as Google, meta, X-corporation, Amazon and AWS, manufacturing companies such as Intel, with an equally distributed professional industry that includes finance and banking, education, commerce, and is home to a diverse group of professionals working within different industries. Given that Ireland is home to these tech giants, how are the Irish professionals' attitudes towards AI technology acceptance? Since societal implications are crucial for the success of AI adoption (Li, Bitterly, 2024), variables such as intelligent process, tech-enabled manpower, cost optimisation, innovation in business, customer satisfaction, firm resilience, business value,

(Sharma, Kumar, 2024), only provide a partial analysis of the factors that impact AI adoption within businesses.

It can be gathered, based on the research, that AI enables businesses to gain competitive edge within the industry and its increasing accessibility is an advantage to many, however, there is an evident lack of research whether the overall attitude of professionals are in line with the optimistic overview that is presented in the literature.

Digital technologies are constantly evolving and improving rapidly, and to benefit from these technologies, it must be adopted by the organisations successfully, through strategic alignment which may be achieved through synchronised change in strategies (Zeebroeck, Kretschmer, Bughin, 2023). Ye, Khanna and Paulson (2024) present how technological uncertainty reduces adopters' willingness to adopt new technology. AI technology, which is one of the most popular driver of change in the workforce today, was actually first introduced in the 1950s and by the 1960s was "effectively liquidated" due to the slow progress against what was expected (Raisch, Krakowski, 2021), only to have met the expected leading position in the 2020s.

Based on the research presented by Ye, Khanna and Paulson (2024), this would mean AI technology adoption is uncertain and therefore adoption must be negatively impacted, however, literature presents and it can also be observed that AI technology is indeed intertwined with our daily lives in one way or another.

Uncertainty is therefore not the only factor affecting AI technology adoption. It is important to understand the factors that impact the acceptance of technology, to develop resilient and sustainable strategies that enables technology adoption that contributes to the competitive advantage for the firms, but every firm has employees, humans that work towards creating the value propositions for businesses to succeed in the industry. Swan and Newell (1994) argued that the success of technology adoption is led by and driven by the managers' beliefs about the factors that affect the adoption. Since leadership, by definition, has an impact on the overall efficiency and effectiveness of the individuals working within a firm, the factors that impact the employees must be critically assessed and understood to assist AI technology adoption in the current times. Vasiljeva and Lulle (2021) further have presented, through survey-based research, top managements attitude, competition and regulations are the three main factors that impact AI adoption in an organisation. Studies show there's a direct correlation between individual, perceived usefulness

and managerial support, positive attitude in employees, which can be developed through educational attainment, and individual demographic factors are directly correlated with technology adoption (Talukder, 2012; Qazi, Talukder, 2011). The studies presented so far are generally focussed on managerial perspectives and the role of top management, however, research focussed specifically on general AI technology adoption from an individual/employee perspective is unaddressed. For managers to make the right decisions, it is important to gather insight into how Irish employees/professionals in general are reacting towards AI technology and further enable AI technology acceptance.

Technology adoption is the acceptance and use of new technology (Mkhonto, Zuva, 2023) and the models and theories of technology adoption have evolved to explain or evaluate the acceptance and use of the technology, at individual and organisational levels (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014). One of the most widely accepted, and with a 70% accuracy of predicting this behaviour, is the Unified Theory of Acceptance and Use of Technology, proposed by Venkatesh (2003). It is considered a comprehensive model that helps evaluate how people may accept or reject the technology being introduced, and has been widely used amongst researchers to evaluate the acceptance of specific technology developed using AI (Williams, et al., 2015; Veronica, Surja, 2023; Sheikhtaheri, 2024; Adj, et al., 2024), there's scant research focussed on the technology acceptance of AI in general, as a technology (Gerlich, M., 2023).

The study aims to evaluate the perception of professionals working within Ireland towards general AI technology adoption and their overall attitude towards accepting this technology. This has been achieved through quantitative analysis, by means of various statistical analysis techniques, grounded in UTAUT model, gathering primary data through a survey questionnaire used for global study by Gerlich (2023) for evaluating the perspective towards AI technology, across the globe. Statistical analysis was performed using IBM software "Statistical Package for Social Sciences (SPSS)", to identify the correlations between factors, variables and moderators. The study uses Linear regressions, cross-tabulation, factor analysis, descriptive statistics, mean values, KMO-Bartlett's test, Chi-Square tests, rigorously to identify these correlations and draw insights from the survey to evaluate the factors that impact the public perception of professionals working within Ireland, examine the correlations, derive a baseline model grounded in UTAUT, and answer the research questions.

The study presents a literature review, firstly presenting the current AI related literature, followed by a comprehensive section discussing the various technology acceptance theories and models, a further detailed discussion of the UTAUT model, presenting the seminal work of Venkatesh (2003) to discussing the way it has been used by researchers to study other technology adoption. The literature review derives the research question, and the objectives R1, R2, R3.

R1: What factors impact the attitude, of professionals working within Ireland, towards AI technology?

R2: Is there a significant difference between the “western world” attitude and Ireland’s attitude towards AI technology acceptance?

R3: How the factors used for AI technology acceptance study be used with the UTAUT model?

The methods and methodologies section discusses the questionnaire in detail, presents the variables, and the various techniques and tools used for the statistical analysis, and presents the baseline model used for the study, derived from the literature review.

The results section presents the findings of the data analysis, while the discussion section is where these findings have been discussed further, ending with the conclusion and recommendations for future research in this area.

To contextualise the study, the next section starts with the literature review of relevant research.

## 2.Literature Review

The following section provides a literature review of the current state of research in the field of AI technology in business management. It is important to review the broader research landscape around artificial intelligence technology, the business applications of AI, important models and theories of technology acceptance, and extant of literature available specifically for AI technology acceptance, to contextualize this study and synthesize the previous findings to build this study’s research aims and objectives, while deriving the research design.



## 2.1 AI Technology and their Applications in Businesses

Artificial intelligence (AI) is one of the most trending topics of research at the moment, not only from the technological perspective but there's an increased attention from a business management perspective towards AI (Raisch, Krakowski, 2021; Li, Bitterly, 2024; Sharma, Kumar, 2024). AI is intrinsically changing the way the world has been operating. While there are benefits such as higher data accuracy, lower rate of errors, lack of personnel dependency and increase in overall efficiency and effectiveness of businesses around the world (Oyekunle, Boohene, 2024; Jorzik, P., et al, 2024), giving businesses a competitive edge, the fear around AI taking over jobs cannot and should not be neglected. Artificial Intelligence is the technology that uses algorithms, large datasets, and tools such as machine learning to automate tasks that would otherwise take more time and resources to be done by an unassisted human (Stoica, L.C., 2022). Organisations around the world work towards optimal efficiency and effectiveness, and therefore the advent of AI has enabled businesses to explore areas where AI can be used to achieve a competitive advantage within the industry.

The pace at which technology is evolving is unparalleled, and AI is being used in industries such as finance, banking and insurance, e-commerce, manufacturing, business management, healthcare, government monitoring, security and many more avenues (Oyekunle, Boohene, 2024; Jorzik, P., et al, 2024; Vanessa, R., 2024; Raisch, Krakowski, 2021; Li, Bitterly, 2024; Sharma, Kumar, 2024; Pallathadka, H., et al., 2023). There are different types of AI and one of the most popularly used one is generative AI or GenAI, which is where text, images, videos, audios, code, and synthetic data can be created using Artificial Intelligence (Vanessa, R., 2024).

Although literature seems to have presented an overall positive attitude towards AI and effectively shares the possible benefits, with a much bigger unexplored potential, AI still lacks the sentimental or rather the emotional capacity to be compassionate. Research presents either the likely use of AI in industries or how they are currently being used, there's complex coding involved, algorithms used, and specific resources required (Stoica, L.C., 2022) to actually implement AI technology which is a known limitation at present. There is a distinct lack of how this technology may be or is being accepted by people.

Researchers suggest the use of AI is expected to lead to an increased efficiency and effectiveness, and the competitive edge that each company seeks would be achieved through strategic alignment and through artificial intelligence enabled business models, using the data-driven, more accurate, nature of AI, the use of AI and robotics together such as in the case of Amazon, or finding the right concoction of AI and augmentation for international business, and business management (Jorzik, P., et al, 2024; Vanessa, 2024; Raisch, Krakowski, 2021; Geetha, et al., 2023). Stoica (2022) has stated the computational cost of AI tools is reducing, however, they have later stated initial investment is very high, which means AI is accessible only to certain businesses with enough capital. It is not only the initial investment cost that is a challenge, but also the skilled workforce that is required for the integration of AI tools would need higher wages.

AI works from a large dataset, learning and growing through the interactions it has, and there are legitimate concerns around the privacy of the data that is exchanged with AI tools. The “Black-Box” model of AI tools does not offer transparency that is needed to ensure the predictions and outputs generated are accurate, while a “white-box mainly used for banking and financial sectors, offers the transparency that is needed to validate the output” (Tchunte, D., et al., 2023). The white-box models however are artificial narrow intelligence tools, needing higher computational factor and a skilled human to verify the logic used behind these outputs.

Despite the surmountable benefits of AI for businesses, researchers have argued the role of top managers, manager cognition, trust and support from employees, and overall part of humans will be crucial for the AI tools to be used and designed, to achieve the said competitive advantage (Li, Bitterly, 2024; Raisch, Krakowski, 2021; Jankovic, Curovic, 2023; Sharma, Kumar, 2024; Unni, et al, 2023; Oyekunle, Boohene, 2024; Jorzik, et al., 2024).

The use of AI in businesses has been widely accepted, with all the benefits of improving the value proposition, higher data accuracy, data-driven decision-making, and faster fixes, however there’s rather a paradox where AI technology seems to be taking over jobs that were traditionally done by human beings, that might lead to resistance from employees, while being impactful and useful for businesses to optimize their operations. AI must co-exist with humans and vice-versa, for businesses to truly achieve this competitive advantage that is a common goal for firms. While the emotional capacity of AI is discussed as a disadvantage (Li, Bitterly,

2024), it is also important to note that the technology is still developing and is likely to continue improving the capabilities, and therefore may be able to replicate artificial emotional intelligence. There's extensive research that sheds light on the technical aspects of AI technology, and the lack of human sentimentality (Raisch, Krakowski, 2021; Li, Bitterly, 2024), there is limited research on how human beings perceive AI within their industries and the impact it has on businesses adopting AI technology. Despite the plethora of technology acceptance models and theories (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014), there is scant research on the acceptance of general attitude or acceptance towards artificial intelligence technology. The evolution of AI is reducing the human dependency of predictive analysis, this will in turn affect all business sectors eventually.

Ångström, (2023) through their survey and interview-based research identified the main challenges faced by organisations were technological, organisation structure, and cultural. If that is the case, as per Ghemawat (2005) the world would be adopting AI technology differently, and the challenges faced would also vary, implying a more geographically focused study being imperative to understand the factors affecting AI technology adoption.

## 2.2 Technology Adoption Theories and Models

Technological innovation has been discussed as a crucial factor for businesses to succeed, and to gain the competitive edge in the market, however, this technology must be accepted and utilised by consumers and employees to attain that competitive edge.

Technology adoption is the acceptance and use of new technology, and the models and theories of technology adoption have evolved to explain or evaluate the acceptance and use of the technology, at individual and organisational levels (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014). These theories and models of technology adoption can be used to understand the acceptance and use of AI technology. Research and development in the field of Artificial intelligence is currently increasing, with more focus on its learning capabilities and ethicality, although for any technology to be sustainable, it must be accepted and used by people, hence it is important to study the adoption of AI among professionals from varied backgrounds.

Technology adoption is the behavioural intention and actual behaviour of an individual, towards ultimately the acceptance and usage of this new technology. The theories and models have evolved from one another, throughout the years of research into this domain (Mkhonto, Zuva, 2023), that may help determine the success of evolving technology being introduced in the markets. Mkhonto and Zuva (2023) have mentioned these models and theories to be the tool that allows researchers “foretelling” opportunities about the behaviour of individuals towards acceptance of technology. The **theory of reasoned action** (TRA) (fig.1), proposed by Fishbein and Ajzen in 1975 is one of the earliest technology adoption theory which foretells the acceptance of technology based on the relationship between individual behavioural intention and actual behaviour towards the technology. The researchers found that the behavioural intention has a direct impact on the actual behaviour of an individual interacting with the technology, while the behavioural intention is a construct based on subjective norms and individual attitudes, formed by their beliefs and the likelihood of the individual believing that performing the expected or target behaviour will result in consequences that benefits them (Mkhonto, Zuva, 2023). Most of the work in the field of technology adoption has been based on TRA, and the models and theories that may be found now, have evolved from TRA.

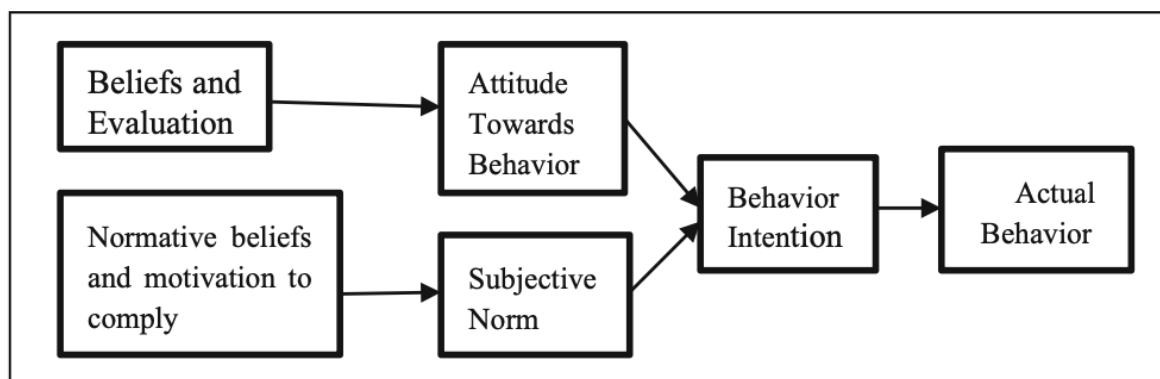


Figure 1: Theory of reasoned action (TRA) (Mkhonto, Zuva, 2023)

While TRA looks at the behavioural intention of an individual towards accepting a technology, it did not account for the volatile nature of “attitudes”, and therefore, Fischer proposed the **theory of planned behaviour** (TPB) where the construct of “perceived behaviour control” was added to the previous TRA model to address the changing attitudes that people have; perceived behaviour control takes into account the factor of “people’s perception of ease and usefulness to perform the targeted

behaviour” (Sharma, Mishra, 2014). It must be noted that technology adoption is a stage within the diffusion of technology, that is, technology adoption models and theories help understand the likeliness of a decision amongst the public about the technology, in simple terms, whether the public would accept this technology or reject it. **The diffusion of innovation theory** was a pioneer work presented by Everett Roger in 1960, where four elements that influenced the spread of a new idea were identified, namely, innovation, communication channels, time and social systems, and five stages within the spread were hypothesised, which included knowledge, persuasion, decision, implementation and confirmation (Fig.2) (Sharma, Mishra, 2014).

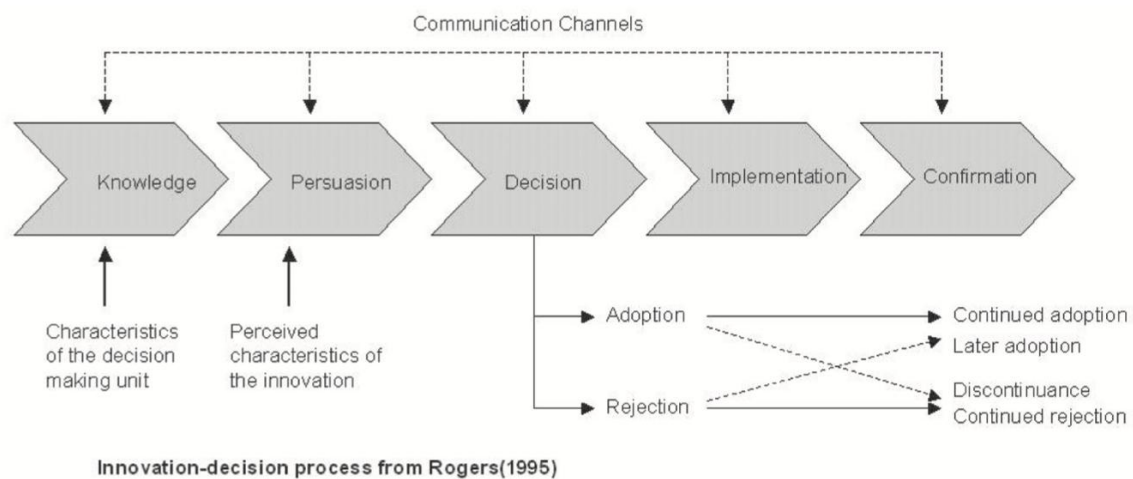


Figure 2: The diffusion of Innovation theory stages (Sharma, Mishra, 2014)

The diffusion of innovation theory presented an S-shaped curve for how the technology is spread and accepted by the population, with time, and later becomes a commonplace understanding, similar to how an infection would spread in the population, the innovation would follow the similar S-curve (fig.3) (Sharma, Mishra, 2014).

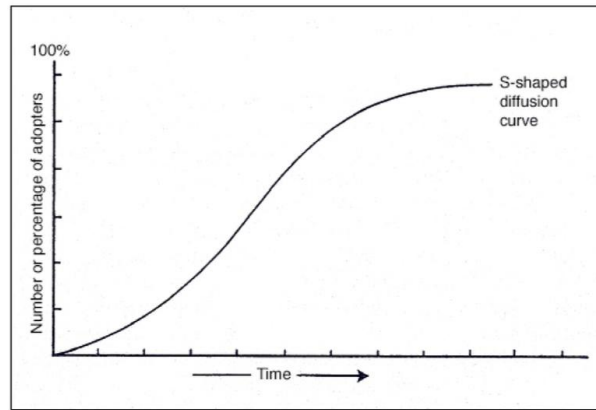


Figure 3: S-shaped adoption curve (Sharma, R., Mishra, R., 2014)

The diffusion of innovation theory looks at the lifecycle of a technological innovation as a whole, whereas the models and theories of technology adaption have been evolving through years of research into the specific *decision* stage within the innovation-decision stages proposed by Rogers in 1960. **Theory of reasoned action** (TRA) developed by Fishbein and Azjen (1975) has been developed further by researchers to include factors that impact the decision-making stage. Azjen (1975) adapted the original TRA model by adding the “perceived behavioural control” construct to form the theory of planned behaviour, which indicated a shift of the technology adoption towards including a behavioural psychology element to it. A few of the most widely used theories and models include, but are not limited to, are Technology acceptance model, Task-technology-fit model, and the Unified theory of technology acceptance and use of technology.

**Technology acceptance model** (TAM), developed by Fred D Davis in 1989 involves psychological factors that affect the technology acceptance amongst population, the model centres on “perceived usefulness” and “perceived ease of use” which determine the user’s attitude and intentions of use behaviour (Fig.4) (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014). Sharma and Mishra (2014), through a literature-based study around technology adoption models and theories, have shown a direct relationship of these new constructs, perceived usefulness and perceived ease of use, to “Bandura’s self-efficacy theory (1982)” and “Rogers and Shoemaker (1971) study in defining complexity, “the degree to which a person believes that using a particular system would be free of effort”.

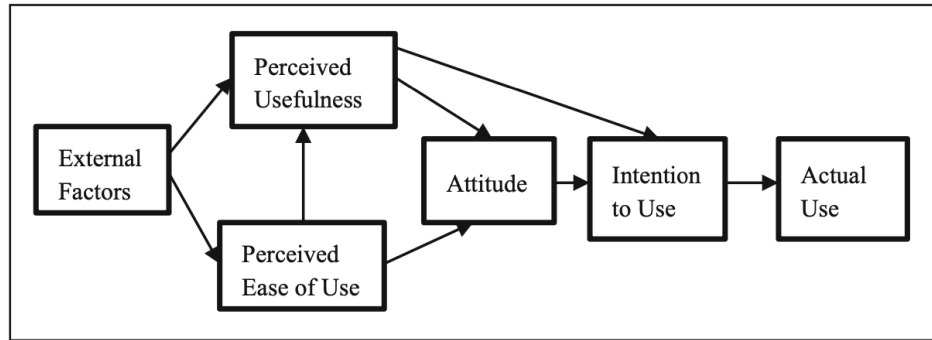


Figure 4: Technology Acceptance model (TAM) (Mkhonto, Zuva, 2023)

Mkhonto and Zuva (2023) through a more recent literary study into technology adoption models have presented TAM and its other modified models TAM2 (fig.5) and TAM3 (fig.6), where similar constructs are used expanding on the factor loading on to perceived usefulness and perceived ease of use constructs.

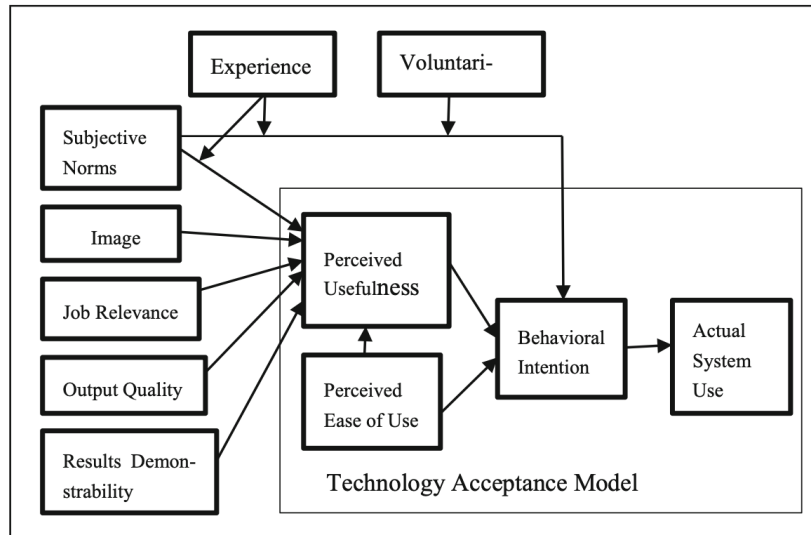


Figure 5: Technology acceptance model2 (TAM2) (Mkhonto, Zuva, 2023)

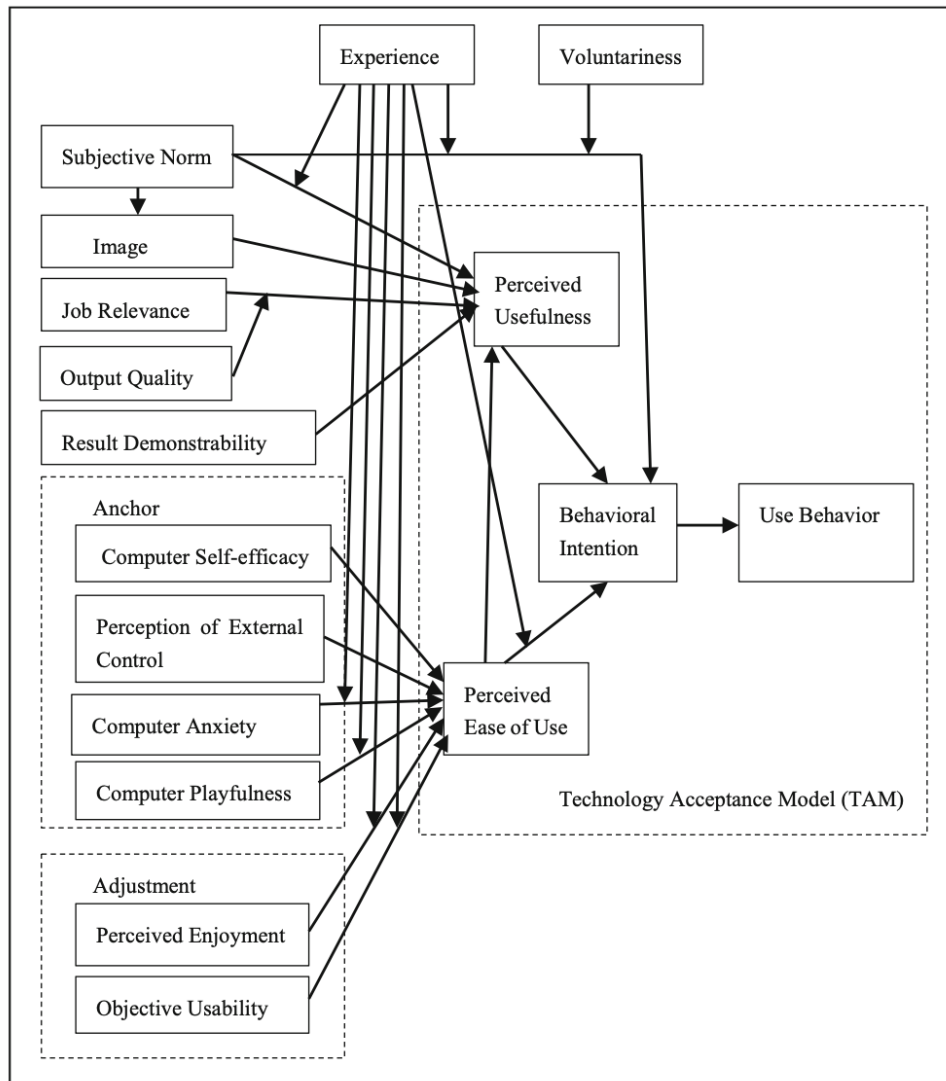
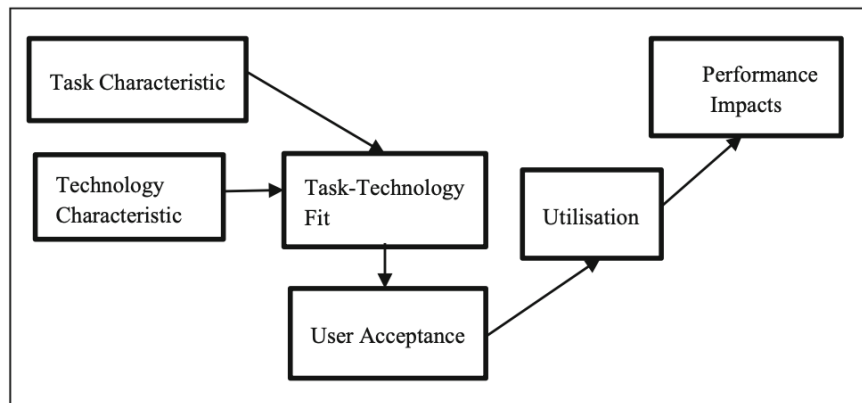


Figure 6: Technology Acceptance Model3 (TAM3) (Mkhonto, Zuva, 2023)

TAM was developed for the information systems industry and it focusses on the technology acceptance at an individual level, while researchers have also criticised the lack of flexibility when it comes to the rapid pace at which technology is evolving, and testing of the TAM models by IBM demonstrated that perceived usefulness is a stronger factor than perceived ease of use in the adoption of said technology (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014). TAM and its modified versions (TAM2 and TAM3) are designed to cater to individual behaviour towards the innovation, with a focus on how the technology can be useful or how easy it could be to use, while the perceived use and perceived ease of use are two of the main constructs within the model, perceived usefulness has been seen as the dominant construct during implementation, this points to a possibility of the model being impactful only under specific conditions, thus limiting its versatility.



**Task-Technology-fit** (TTF) model is another model, developed by Goodhue in 1995, specifically for measuring the technology application and implementation in Information technology environment, specifically linking it to the individual performance (fig.7) (Mkhonto, Zuva, 2023). Goodhue defined TTF as “the degree to which a technology assists an individual in performing his or her portfolio of tasks”, implying any technology will only be used if the functionalities support the user in accomplishing their expected tasks (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014).



*Figure 7: Conceptual framework of the TTF model (Mkhonto, Zuva, 2023)*

While the task-technology-fit model is a very closely linking the IT and individual performance related theories together, within the information systems environment, it lacks the foretelling power which the previously presented models could bring, this specific model also lacks the consideration to situational and personal factors, which impacts the ultimate user acceptance behaviour and therefore may be considered for very specific technology and within a rather saturated testing environment, such as within a rigid organisation, implementing a specific technological innovation for its employees. The scale at which TTF might be utilised is very limited, based on the detail discussed above.

If we look at TAM as the centre of where technological innovation links with the social-cultural work settings, to create a model for technology acceptance, TTF would lean towards a more technical side within that spectrum, while given that TAM eliminates the subjective norm (social construct) of decision making, if one moves in that spectrum more towards the original behavioural psychological parameter, UTAUT would be the result (fig. 8).

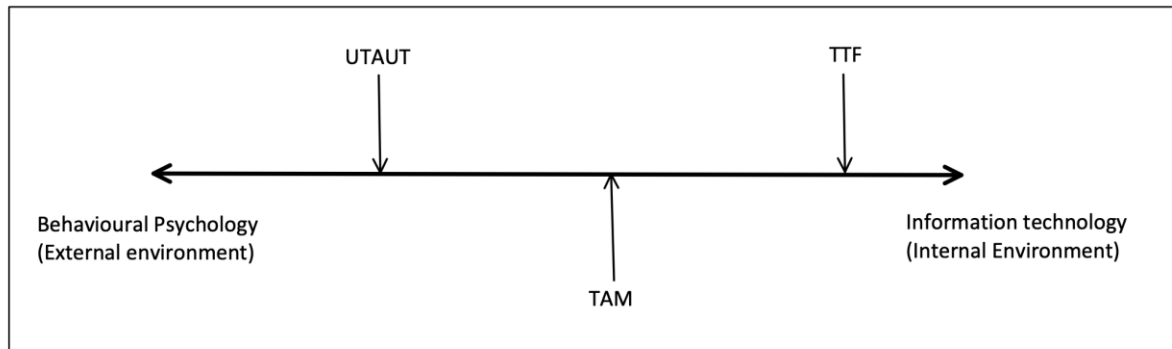


Figure 8: Development spectrum from TAM to UTAUT and TTF

**Unified theory of acceptance and use of technology (UTAUT)**, proposed by Venkatesh, et al., in 2003, is the most widely used technology adoption model, in the field of general technology acceptance models, which aims to address the lacunas of the previous models; it is regarded as the “superior model”, with a prediction accuracy of 70%, unmatched by any other models (Mkhonto, Zuva, 2023). Unlike other technology adoption models, UTAUT takes into account the fact that some systems are mandatory while others are voluntary, including dependent and independent variables such as gender, age, performance expectancy, effort expectancy, social influence, facilitating conditions, all contributing to the user’s behavioural intention and the actual use behaviour (fig.9) (Mkhonto and Zuva, 2023; Sharma, Mishra, 2014).

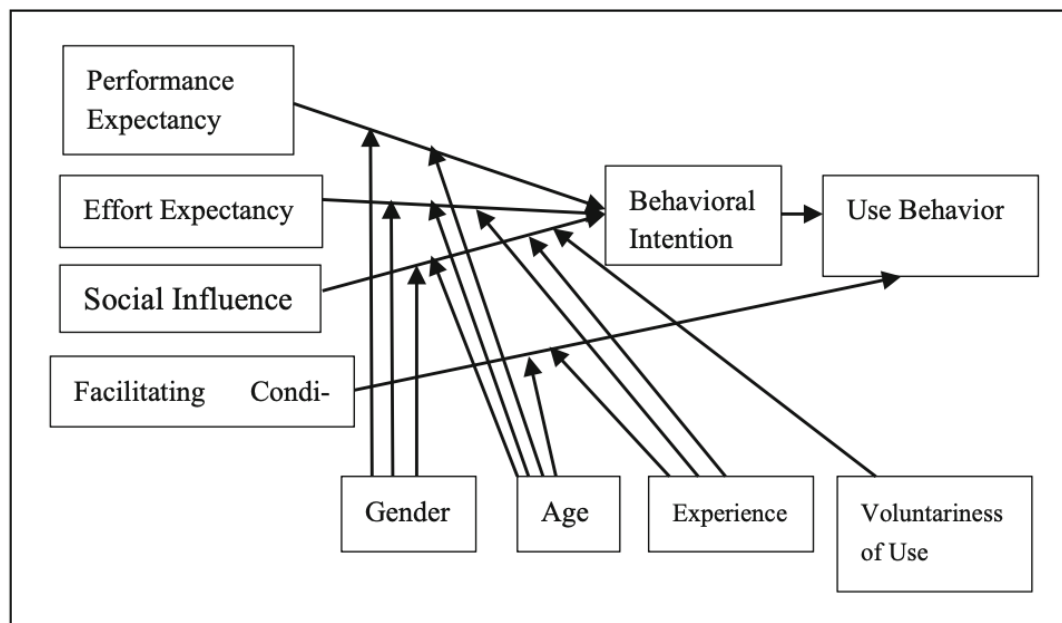


Figure 9: Unified Theory of Acceptance and Use of Technology (UTAUT) (Mkhonto, Zuva, 2023)

Despite the over-complexity of the UTAUT model, and inability to explain individual behaviour, which has been criticised by researchers (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014), UTAUT is ideal for general technology adoption studies, which is the goal of this research. Unified theory of acceptance and use of technology addresses the weaknesses found in the other models, provides the highest prediction accuracy of user behaviour towards general technology adoption, and considers both the behavioural and technical aspects towards the decision-making stage within the innovation diffusion life cycle.

## 2.3 Unified Theory of Acceptance and Use of Technology

Technology has been rapidly evolving and has become a prominent area of capital investment, as mentioned previously, for organisations to maintain a competitive edge, it is important to continuously evolve and adapt technology utilised for operations. Venkatesh et al, (2003) noted the dramatic expansion within the information systems industry since the 1980s and the importance of these expanding technological innovations to be accepted by users within organisation to increase productivity, however, with the rapid technological development, several models and theories of technology acceptance were developed. Some of these models have been discussed in the previous section, although, it should be noted that these are not the only technology acceptance models and theories that exist.

The models and theories of technology acceptance have their roots in information systems, psychology, and sociology, capable of accounting for 40% of variance in individual technology use intention (Venkatesh et al, 2003). Despite the plethora of models and theories available, researchers had to “pick and choose” the constructs to use amongst various models or choose a “favoured model” while denying the opportunity to use constructs from other models, this led to the need of a more unified theory, consisting of a comprehensive approach to predicting behavioural intention and actual use behaviour, proposed as the Unified Theory of Acceptance and Use of Technology (Venkatesh, et al., 2003; Williams, 2015; Mkhonto, Zuva, 2023; Sharma, Mishra, 2014). This should mean UTAUT is the most ideal model to predict technology acceptance and use behaviour among population, and yet, very little research can be found with UTAUT model to examine public perception towards general AI technology.

The theory was developed by reviewing eight dominant models and theories of technology acceptance, namely, TRA, TAM, the motivational model, TPB, combined TPB/TAM, the model of PC utilisation, innovation diffusion theory, and social cognitive theory (Venkatesh et al, 2003; Williams, et al., 2015). Venkatesh (2003) in their seminal work identified the weaknesses within the models, and ensured, unlike previous models and theories, the technology studied would be more organisational and not individual oriented, used data collected from employees in an organisation, technologies from the time of initial introduction though more familiar stages were tested, both voluntary and mandatory usage contexts were tested. UTAUT model uses 4 direct determinants of user acceptance and usage behaviour with 4 key moderators, namely, *gender, age, experience, voluntariness of use* (Venkatesh, et al., 2003) (Table 1):

Constructs	Definition	Moderators
Performance Expectancy	the degree to which an individual believes that using the system will help him or her to attain gains in job performance.	Gender and Age: “especially salient to men”; Younger workers likely to be more driven by performance expectancy.
Effort Expectancy	the degree of ease associated with the use of the system.	Gender, Age, Experience: “Effort expectancy more salient for women than men”, “Increased age associated with difficulty in processing complex information on the job.”
Social Influence	The degree to which an Individual perceives that important others believe he or she should use the new system.	Gender, Age, Voluntariness, experience: “stronger effect for women, particularly older women in mandatory settings in

		the early stages of experience.”
Facilitating Conditions	the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.	Age and Experience: “Older workers attach more importance to receiving help and assistance”

*Table 1: Direct determinants of user acceptance and usage behaviour in UTAUT as defined by Venkatesh et al., 2003; compiled in a table by author.*

As presented in table 1, the moderators for each construct have been studied with a specific hypothesis towards the impact of gender, age, experience, and voluntariness, on the four constructs within UTAUT.

UTAUT has been acknowledged as the most comprehensive technology adoption models (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014) on the contrary however, Williams (2015) through a literature review of UTAUT, found that the model has primarily been used for technology adoption and acceptance research in the areas of e-government, e-banking, e-learning and e-commerce, while there is ample scope for original research using UTAUT. There is clearly a disconnect between the intention with which the UTAUT model was developed and the practical use of it today.

The model has been used for specific technology (Sheikhtaheri, A. *et al.* 2024; Adji, 2024; Veronica, 2023) despite Venkatesh’s seminal work being based on the foundation of addressing the weaknesses of other theories and models of technology adoption, and researchers Mkhonto and Zuva (2023) and Sharma and Mishra (2014) stating UTAUT being a “general technology model”, however, recent studies using UTAUT (Sheikhtaheri, A. *et al.* 2024; Adji, 2024; Veronica, 2023) are still presenting a similar trend as noted by Williams (2015), with the model being primarily used for specific technology.

Sheikhtaheri (2024), studied Nurses’ attitude towards patient safety reporting system, Veronica (2023), used UTAUT to understand the adoption of mobile application, or Adji’s (2024) Analysis of the Robo-Advisor Investment Applications on Investor Satisfaction using UTAUT, these are all different technological innovation, for different industries, using the same model. It is important to acknowledge the fact that although the same technology adoption model is being used in all three

researches, the original UTAUT model has been adapted/modified as per the need of the research, therefore, it can be said that the model, despite its underutilised capacity, is extremely versatile and offers flexibility.

The use of UTAUT to evaluate general technology, such as artificial intelligence, is currently quite limited. Literature shows the latent capacity of UTAUT as a dynamic model that may be used to foretell the behavioural intention and actual behaviour of users, towards AI. The moderators defined by Venkatesh (2003) during the inception of the model used hypothesis built on the gender, age, and socio-economic landscape, which was a decade ago, moreover, the social-cultural differences between geographies, which impact the direct determinants or constructs of the UTAUT model, should not be neglected. The research therefore aims to use UTAUT model to understand the public attitude, among Irish professionals, towards artificial intelligence acceptance. Artificial intelligence has the potential to change the nature of our workforce, labour demands, and our day-to-day interaction with technology, the widespread popularity of AI, as discussed previously, also means that the attitudes of citizens towards AI technology must be studied, for organisations, managers and researchers, to keep up the competitive edge. Gerlich (2023) investigated the attitudes of citizens towards AI in developed and developing countries, given that each market has its own set of unique challenges and opportunities, socio-cultural differences, this study aims to investigate the attitudes of professionals working within Ireland, towards AI technology, based on the most comprehensive technology acceptance model UTAUT and its constructs and moderators as detailed above.

### 3. Research Question

The current research landscape has revealed a lack of studies, examining the public perceptions, which contribute towards the decision making towards accepting or rejecting a technology, albeit the exponential increase in the research and development of Artificial Intelligence technology, a technology is only a success when the general public accepts it. Organisations around the world seek a competitive edge, which is linked to adapting and utilizing technology effectively and efficiently. While organisations wish to maintain this competitive edge, and research presented above has uncovered the various technology acceptance models and

theories, there is still a lack of research focussed on understanding the public's perception towards AI technology, not the specific tool being developed by the use of AI but the overall general technology of artificial intelligence as a whole. This study aims to use UTAUT model as the foundation to evaluate the technology acceptance amongst professionals working within Ireland, while building on the research by Gerlich, (2023), on a national scale, to gather insight into public's perception and attitude, further enabling strategies to mitigate resistance towards AI acceptance.

Key questions addressed in this research include:

R1: What factors impact the attitude, of professionals working within Ireland, towards AI technology?

R2: Is there a significant difference between the “western world” attitude and Ireland's attitude towards AI technology acceptance?

R3: How the factors used for AI technology acceptance study be used with the UTAUT model?

The study used the original questionnaire as presented in Gerlich's (2023) study of Western (USA, UK, and Europe) perceptions and attitudes towards AI, while using statistical analysis techniques and tests to answer the research questions.

## 4. Methods and Methodologies

The study uses a quantitative analysis method, combined with a literature review to draw inferences within the technology acceptance of Artificial intelligence. Online survey questionnaires, according to Saunders (2019) are ideal for researches focused on examining attitudes, which has been chosen as the method of primary data collection. The online survey allows for self-completion by the participants, meaning this study remains a non-experimental approach, where the researcher does not influence the results in any way, maintaining the unbiased validity of the primary data, while a non-experimental design allows enables analysis of the connections between variables (Gerlich, M., 2023). The survey questionnaire (Appendix A) was circulated among professionals working within Ireland, using a snowball sampling strategy, allowing the possibility of varied demographic data and perception data to be gathered, for correlational study. The survey used was published originally in the study by Gerlich (2023) at a global scale, and therefore is considered validated. The questionnaire included questions about demographic

characteristics such as gender, age, highest education level and income level, and questions gathering perception/attitude related data on a 6-point Likert-scale, limited to professionals working within Ireland only.

A total of 113 responses were recorded, however, only 21% of these participants answered open ended, free text, questions, therefore these have been discarded from the study at this point. The total sample size is rather small, is biased in terms of the demographic data gathered, which must be acknowledged. This has been further discussed in the results section, below.

The statistical analysis of this data, to perform correlation testing, factor loading analysis and model fit testing, has been done through the IBM software Statistical Package for Social Sciences (SPSS). The study firstly uses the same structure as used by Gerlich (2023) in their study of “Perception/attitude of people in Western countries”, where the questionnaire (Appendix A) has been grouped as below:

Demographics:

- Age
- Gender
- Education level
- Income level

Perceived benefits of AI:

- Increases efficiency and accuracy;
- Offers convenience and saves time;
- Improves decision-making processes;
- Helps solve complex problems;
- Leads to cost savings;
- Creates new job opportunities.

Perceived Risks of AI:

- Leads to job displacement;
- Violates privacy concerns;
- Used for malicious purposes;
- Causes errors and mistakes;
- Perpetuates bias and discrimination;
- Unintended consequences.

Trust in AI:



- Performs tasks accurately.
- Makes reliable decisions.
- Is predictable.
- Confidence in AI's ability to learn.
- Keeps my personal data secure.
- Used ethically.
- Less or no personal interests compared to humans.

#### Governmental/societal issues:

- The government does not solve important issues like climate change.
- AI can help address societal issues such as climate change and social inequality. Governments cannot solve global issues.
- AI has the potential to solve global issues.
- Politicians and countries have too many vested interests.
- AI has the potential to make society more equitable.
- AI can help create solutions to societal issues.

#### Usage of/exposure to AI:

- Use AI-powered products and services frequently.
- Basic understanding of what AI is and how it works.
- Zero experience with AI.
- Comfortable using AI-powered products and services.
- Encountered issues with AI-powered products and services in the past.

#### Cultural influence and AI:

- Cultural background influences my attitudes towards AI.
- Different cultures may have different perceptions of AI.
- AI development should take cultural differences into account.
- Cultural beliefs impact my level of trust in AI.
- Cultural diversity can bring unique perspectives to the development and use of AI.

#### Future perspectives:

- AI is the future of humankind.
- AI is the end of humankind.

A combination of descriptive statics and linear regressions have been used to compare the results of Gerlich's findings (2023) with Ireland specific responses,

using the same variables and hypothesis. To analyse the data using aforementioned statistical software SPSS, the Likert-scale values were modified using a scoring system where 1 represented “Completely disagree” and 6 represented “Completely agree”. Responses were reverse coded for questions with negative framing, e.g. “AI is the end of humankind”. Mean and frequency statistics were used to analyse the data, with linear regression to determine the correlation between demographic factors (moderators) and variables (constructs). The questions were combined to get an average score, for the variables defined, as above. The calculations followed the arithmetic formula:

$$(\text{Sum of questions within a variable}) / \text{Number of questions}$$

e.g. for the variable defined as “future perspective” the questions (AI is the future of humankind + AI is the end of humankind) / 2 would create the new variable with the mean average scores, used for the analysis.

The descriptive research is grounded in the unified theory of acceptance and use of technology, and therefore the same survey responses have been used to create a modified UTAUT model, with the constructs Facilitating conditions (FC), Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), Behavioural Intention (BI), Actual Use Behaviour (Use) and Trust (fig. 10), which has been tested using factor analysis, through Principal component analysis extraction method, and Varimax with Kaiser Normalization Rotation method, to evaluate the factor loading, latent factors and correlations, resulting in 6 rotation converged iteration, using SPSS.

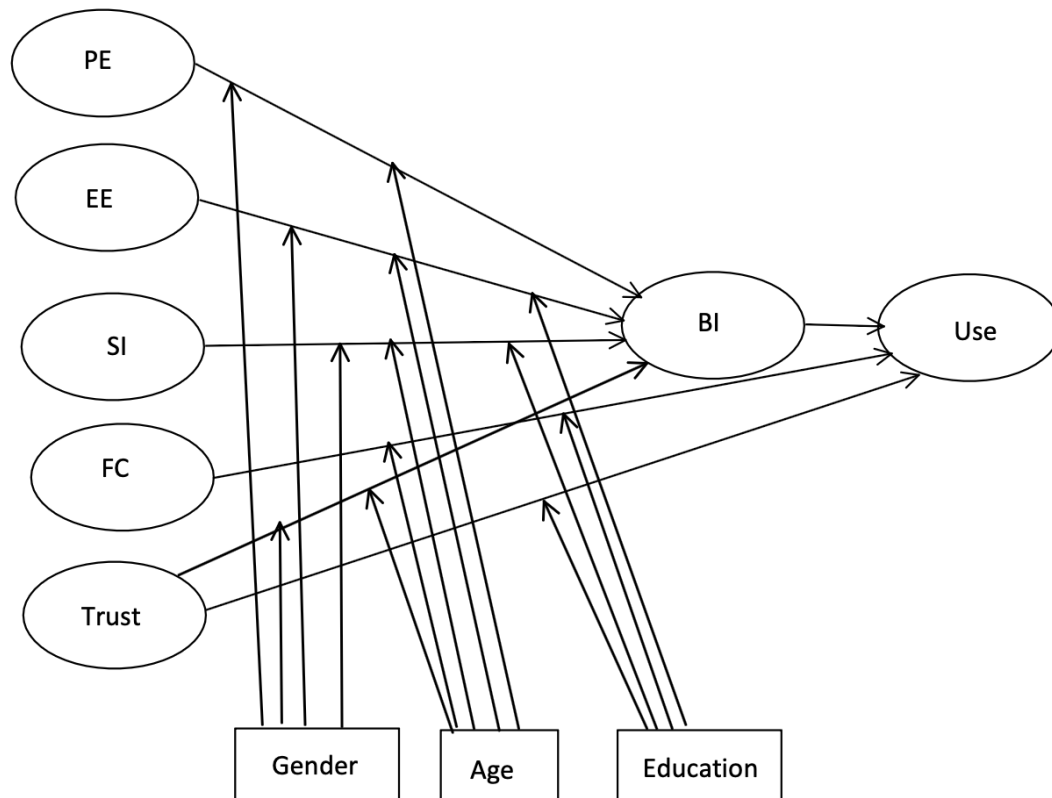


Figure 10: Baseline model adapted from UTAUT and Gerlich's survey variables

Using the baseline model (fig.10) and the variables identified through factor loading analysis, the model has been verified, presented in the results section. Sheikhtaheri (2024) has noted an ambiguity when it comes to the ideal value of factor loading, items with factor loadings less than 0.5 were excluded. The construct reliability was evaluated internally through metrics like Cronbach's alpha, which is expected to be higher than 0.7, coefficient beta values corresponding T-values, notably exceeding 2, with P-value exceeding 0.05 were considered significant.

The participants are informed about the intentions of the survey, and a brief about the research, and survey seeking no identifiable data about the participants, is shared at the beginning of the survey (Appendix A). While the data gathered intends to examine demographic factors, it does not need individual identity to examine the overall attitude of professionals/employees, towards AI technology in order to evaluate the factors impacting AI technology adoption within Ireland, therefore anonymity is maintained. The research does not target any vulnerable groups, and only intends to study the overall attitude among professionals within Ireland.

## 5.Findings

### 5.1 Demographic Analysis

The sample consisted of 113 participants, with a fair proportion within genders (Fig.11), men accounting to 54%, while women accounted for 42.5% and non-binary accounting for 3.5%, however, there were significant bias within the Age distribution within the sample (Fig.12) with a dominating 41.6% from the age group 35-44. A similar bias was found in the education level data where 46% respondents had the highest level of education as Masters (fig.13), and Income level distribution being dominated by the ranges “under 50,000 Euro” at 46% and “50,000 to 100,000 Euro” at 40.7% (fig.14).

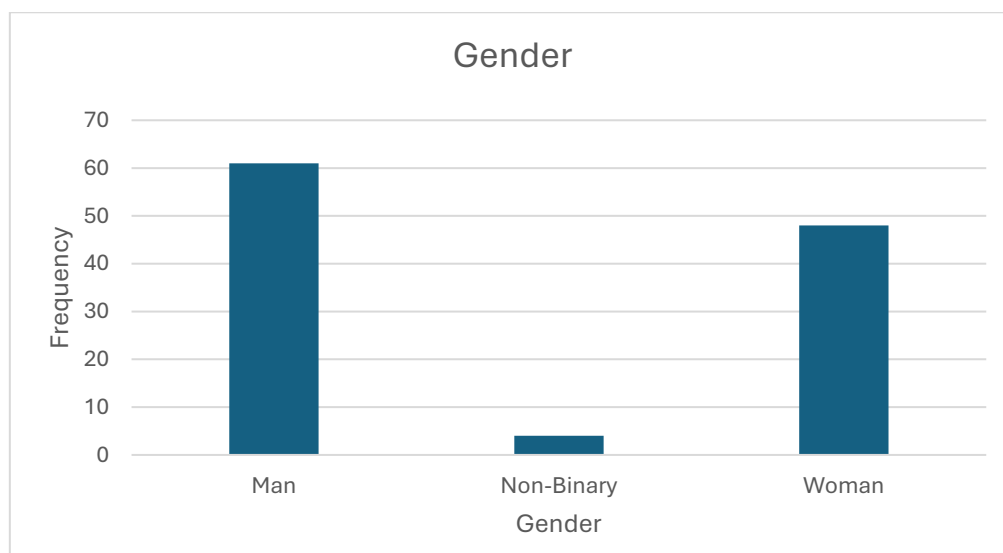


Figure 11: Gender frequency survey data

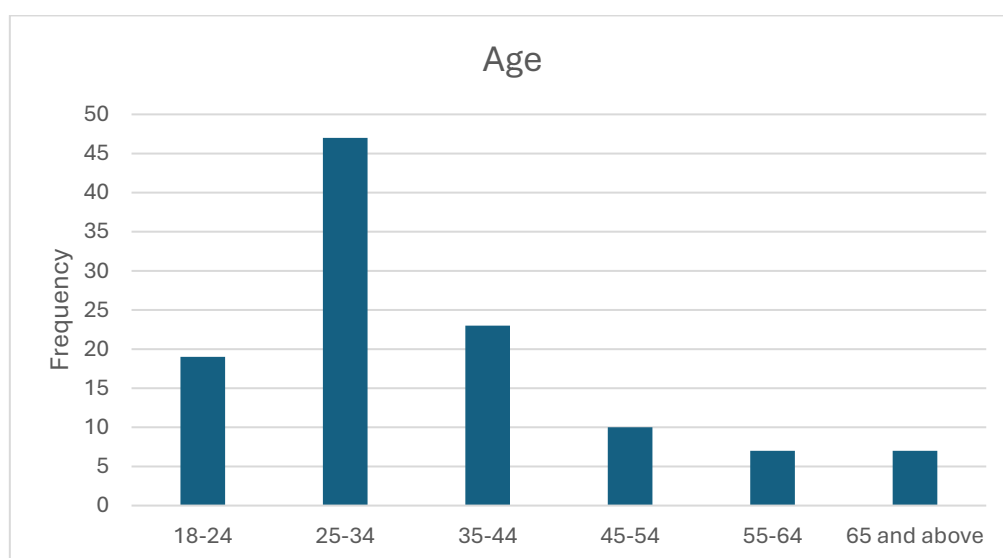


Figure 12: Age frequency survey data

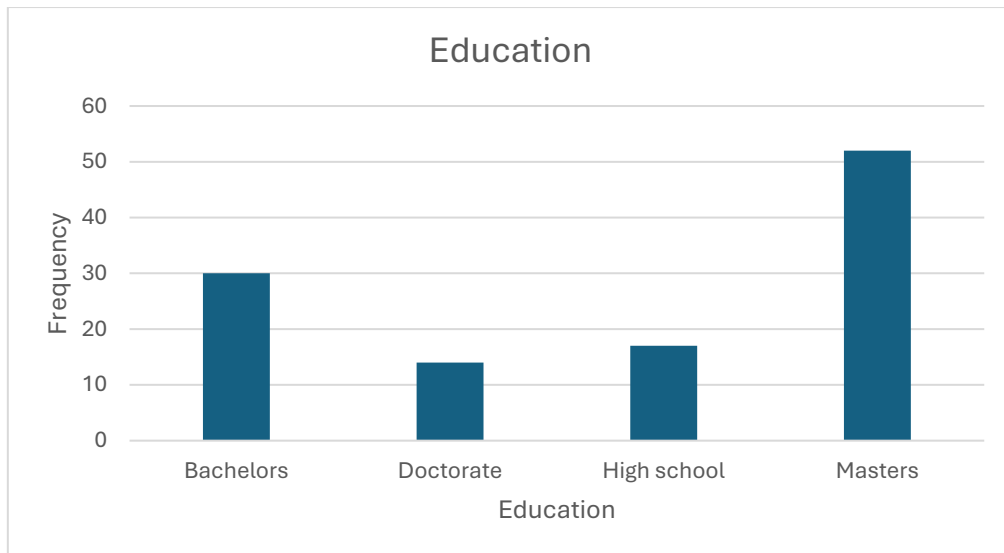


Figure 13: Education level frequency survey data

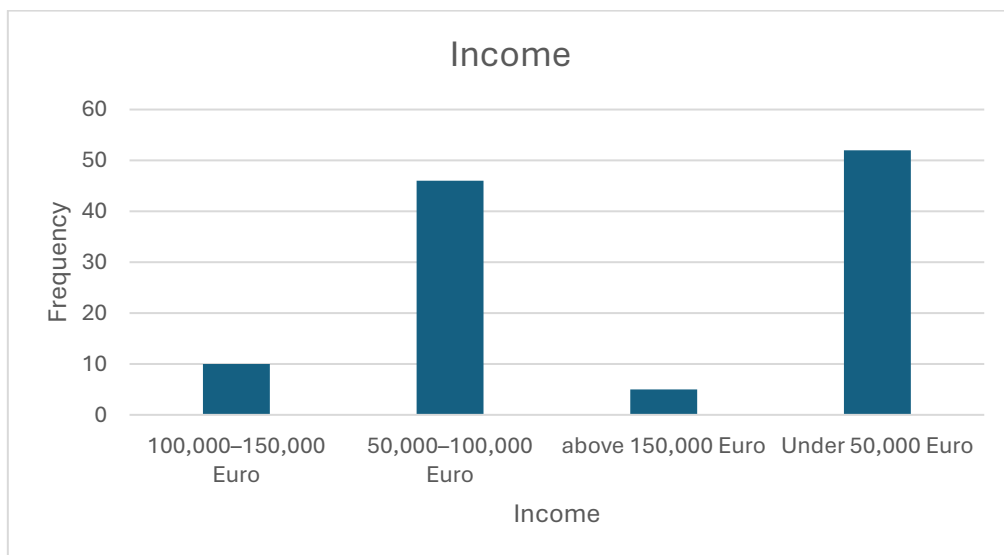


Figure 14: Income level frequency survey data

## 5.2 Demographic impact on Attitude towards AI

The study that is being replicated here, by Gerlich (2023) was done on a global scale, where countries were the differentiating factor, and mean values for each country were compared. Since the setting for this study has been localised to Ireland only, the same regression testing, comparing country-wise perception towards AI, is not possible, hence a cross-tabulation analysis has been performed. The mean value of the question “AI is the future of mankind” is 4.63 (Table.2), which shows a positive inclination overall attitude, independent variables CAttAI, and CTrstAI incline towards a neutral attitude.

### Descriptive Statistics

	Mean	Std. Deviation	N
AlfutMK	4.63	1.434	113
AI_B_Und	4.81	1.076	113
ComfAI	4.68	1.112	113
CAttAI	3.48	1.452	113
CTrstAI	3.39	1.503	113

Table 2: Mean values for variables used in regression 1, testing hypothesis from Gerlich's (2023) study

The impact of Gender (fig. 15), Age (fig.16), Education level (fig.17), and Income level (fig.18) can be seen below, found through cross tabulation analysis, using SPSS.

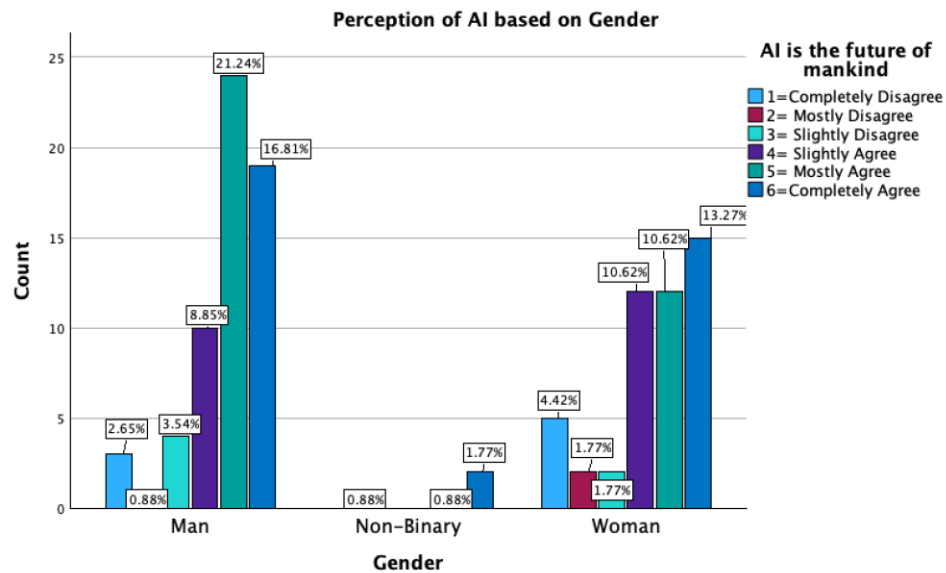


Figure 15: Perception of AI based on Gender

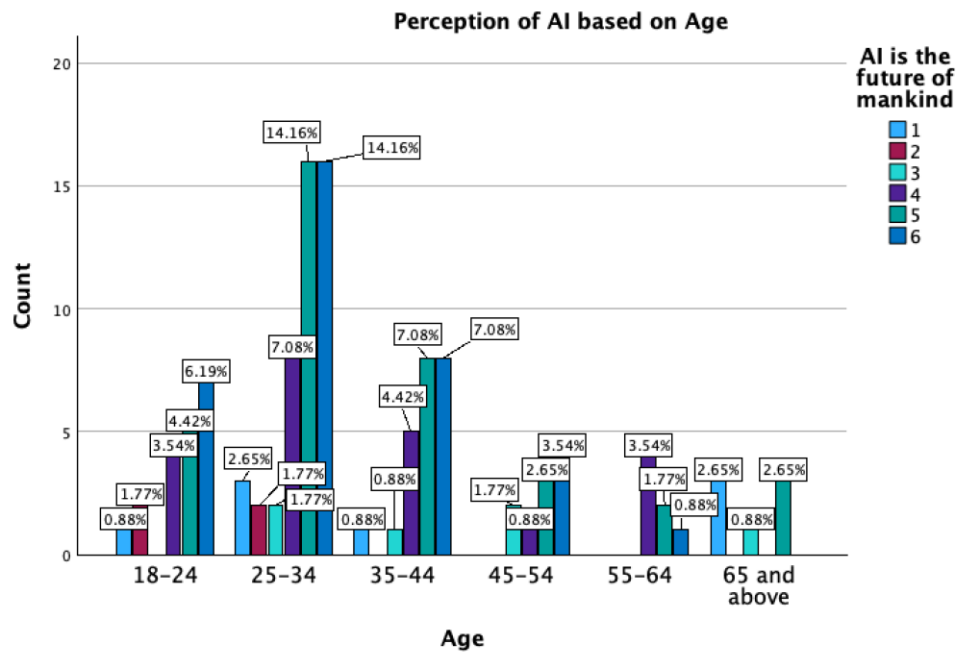


Figure 16: Perception of AI based on Age

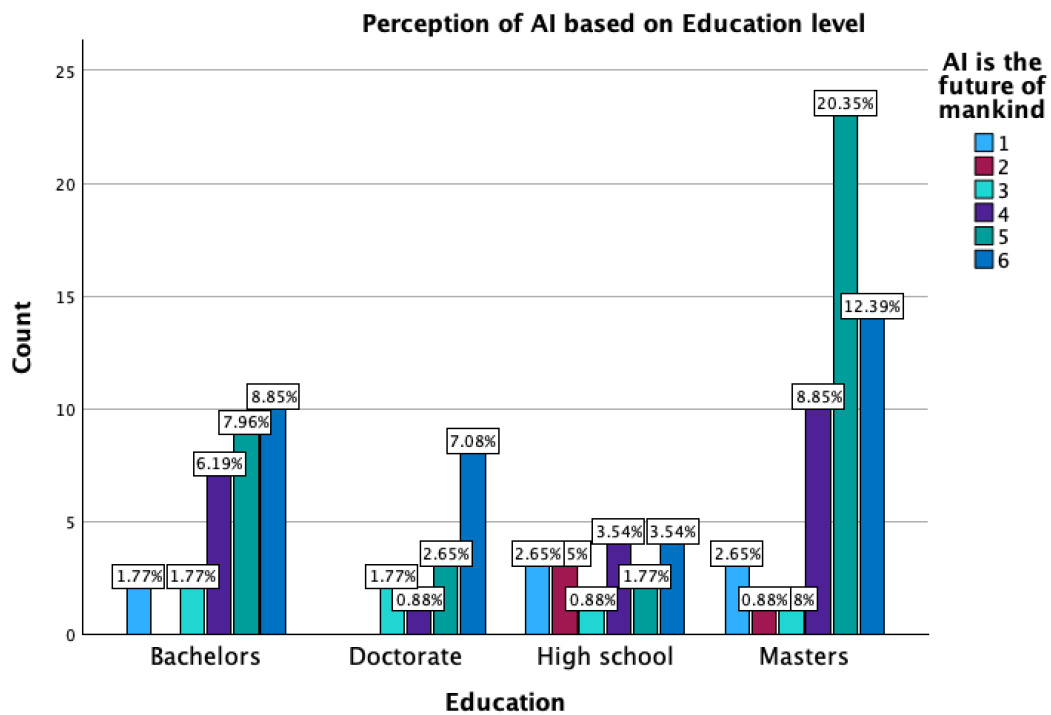


Figure 17: Perception of AI based on Education level

The Chi-Square tests performed on each cross tabulation shows Education level has a significant impact on the perception of AI, with p-value 0.017, df value pf 15 and Pearson Chi-Square value of 28.730 (Appendix B, 69).

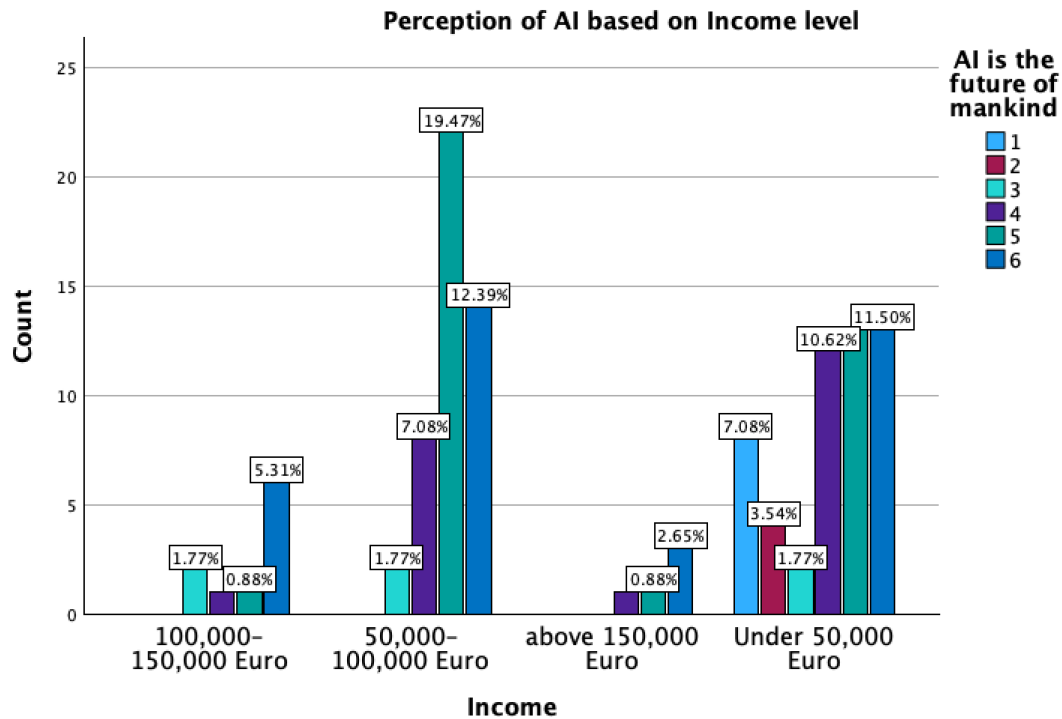


Figure 18: Perception of AI based on Income Level

Income level shows a significant impact on the perception of AI, verified through Chi-Square test value of 30.109, df 15, and p-values of 0.012 (Appendix B, 69).

To compare the results, the dependent variable “AI is the future of mankind” (AlfutMK), question from the questionnaire has been taken as the dependent variable, while the independent variables are kept the same for regression testing, namely, Basic understanding (AI\_B\_Und), Comfort level (ComfAI), cultural aspects (CAAttAI), and beliefs of the respondent (CTrstAI). The hypothesis being tested through this regression are derived from the original study by Gerlich (2023) and checking if the same hypothesis applies for Ireland specific AI acceptance attitude. These hypotheses can be seen in table 3:

Hypothesis No.	Null Hypothesis	Alternate Hypothesis
1	Basic understanding of AI does not relate to perception that AI is the future of mankind	Basic understanding of AI relates to perception that AI is the future of mankind
2	Comfort of using AI does not relate to perception that AI is the future of mankind	Comfort of using AI relates to perception that AI is the future of mankind



3	Cultural background of people does not relate to perception that AI is the future of mankind	Cultural background of people relates to perception that AI is the future of mankind
4	Cultural beliefs of people do not relate to perception that AI is the future of mankind	Cultural beliefs of people relate to perception that AI is the future of mankind

Table 3: Hypothesis structure

The ANOVA test for the regression showed a significance (Table.4), however, upon further investigation, it can be seen that only the independent variable AI\_B\_Und has a significant correlation, based on the *t-value* and *p-value* as highlighted in Table.5, hence the null hypothesis1 is rejected, while hypothesis 2, 3, and 4 accepted .

ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>94.968</b>	<b>4</b>	<b>23.742</b>	<b>18.934</b>	<b>&lt;.001<sup>b</sup></b>
	Residual	<b>135.421</b>	<b>108</b>	<b>1.254</b>		
	Total	<b>230.389</b>	<b>112</b>			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), CTrstAI, AI\_B\_Und, CAttAI, ComfAI

Table 4: ANOVA test value for hypothesis testing.

Coefficients matrix for all variables used for regression 1, testing hypothesis 1-4

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	.395	.543		.728	.468	-.681	1.472
AI_B_Und	<b>.679</b>	<b>.150</b>	<b>.510</b>	<b>4.539</b>	<b>&lt;.001</b>	<b>.383</b>	<b>.976</b>
ComfAI	.215	.146	.167	1.469	.145	-.075	.506
CAttAI	-.100	.104	-.101	-.961	.339	-.307	.106
CTrstAI	.092	.099	.096	.923	.358	-.105	.288

a. Dependent Variable: AlfutMK

Table 5: Significant independent variable

The model fit test was done on SPSS through a factor analysis, through Principal component analysis extraction method, and Varimax with Kaiser Normalization

Rotation method, to evaluate the factor loading, latent factors and correlations, resulting in 8 rotation converged iteration, for the original data variables (Appendix B, Factor analysis 1). The model fit test using the aforementioned method did not result in the same number of latent factors as it did in the study presented by Gerlich (2023). The factor analysis resulted in 9 iterations, 3 more than what was identified originally for the model. This discrepancy is likely due to the stark difference in the sample size where the model is being used, or the data bias that has been identified within the sample size used for this study. However, the Kaiser-Meyer-Olkin (KMO) with a value of 0.799 indicates good sampling adequacy, suggesting factor analysis may be used here while Bartlett's test of Sphericity shows a significance and a high correlation between the variables (Table.6).

<b>KMO and Bartlett's Test</b>		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		<b>.799</b>
Bartlett's Test of Sphericity	Approx. Chi-Square	<b>4178.253</b>
	df	<b>703</b>
	Sig.	<b>&lt;.001</b>

*Table 6:KMO and Bartlett's Test for Factor Analysis 1 on Gerlich (2023) proposed model*

### 5.3 UTAUT- Bringing the survey variables closer to the original model

The original UTAUT model, proposed by Venkatesh (2003) included the constructs Performance expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Moderators, Age, Gender, Experience, voluntariness of use, however, Trust has been identified as an important moderator for technology acceptance (Vorm, E.S. and Combs, D.J., 2022). Given the validated survey used to evaluate the AI technology acceptance was modified, the moderators have been adapted to Age, Gender, Education, while the construct of trust was added to the baseline model.

A factor analysis was performed on all the variables, which resulted in 5 latent factors, with variables that identify with the constructs defined above (table. 7). Table 7 consists of the rotated component matrix, that evaluates the factor loadings for each correlation between the variables and the factors or constructs. Component 1 has been identified as PE, 2 as FC, 3 as EE, 4 as SI and 5 as Trust. Factor loadings

with rotated component matrix scores higher than 0.5 have been used for the constructs and further analysis.

<b>Rotated Component Matrix<sup>a</sup></b>					
	Component				
	1	2	3	4	5
FlunAccu	<b>.899</b>				
CompProb	<b>.888</b>				
Convnsavetime	<b>.875</b>				
DecMake	<b>.848</b>				
CostSav	<b>.760</b>				
NJobO	<b>.646</b>				
AlGlobs		<b>.923</b>			
AlSocClimChng		<b>.904</b>			
AlSocIss		<b>.848</b>			
Tethic		<b>.526</b>			<b>.508</b>
Al_B_Und			<b>.842</b>		
ComfAl			<b>.730</b>		
NoPers			<b>.684</b>		
AlProdUse			<b>.682</b>		
No_Al					
Iss_Alprod				<b>-.809</b>	
CDif				<b>.764</b>	
CdifCons				<b>.687</b>	
CAttAl				<b>.640</b>	
CTrstAl		<b>.543</b>		<b>.582</b>	
TAccu					<b>.779</b>
TPrecit					<b>.718</b>
TRelDeci					<b>.667</b>
TLearn					<b>.608</b>

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.<sup>a</sup>

a. Rotation converged in 8 iterations.

*Table 7: Model Constructs UTAUT using survey data*

The UTAUT model also has the Behavioural Intention (BI) and Actual use Behaviour (Use), for which the factor loadings were evaluated through a specific factor analysis. Table 8 presents the rotated component matrix for the 2 latent constructs, where component 1 is identified as BI and component 2 is identified as Use.

**Rotated Component Matrix<sup>a</sup>**

	Component	
	1	2
AlfutMK	<b>.095</b>	<b>.850</b>
AlProdUse	<b>.050</b>	<b>.890</b>
AlSocClimChng	<b>.946</b>	<b>.014</b>
AlGlobls	<b>.944</b>	<b>.084</b>
AlSoclss	<b>.916</b>	<b>-.013</b>
Tethic	<b>.600</b>	<b>.253</b>

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

*Table 8: BI and Use Constructs factor loading for UTAUT model using survey data*

## 5.4 Linear Regression analysis for identified constructs

Since the latent factors (PE, EE, FC, SI, Trust) were identified as a combination of survey questionnaire variables using factor analysis, linear regression was further used to evaluate the exact correlational value or factor loading. Through linear regression, the correlation and significance were evaluated further, to fine-tune to baseline model (fig.10).

- There were significant correlations found between PE → BI; significance found between PE → Use however upon closer inspection of the variables within PE, no significance was found.
- There were significant correlations found between FC → BI; significance found between PE → Use.
- There were significant correlations found between EE → BI; however, upon closer inspection of the variables within EE, only AI\_B\_Und has a significant impact on BI; significance found between EE → Use.
- There was no Significant correlation between SI → BI; No significant correlation between SI → Use.
- There were significant correlations between Trust → BI; however, upon closer inspection of the variables within Trust, only TLearn has a significant impact on BI; Significant correlation between Trust → Use, however, only the variable TLearn contributes to this significance.

The above-mentioned statistics have been derived from ANOVA model from each linear regression tested (Appendix B, 2-68) along with the p-value and t-value (Appendix B, 2-68).

## 5.5 Hypothesis testing with UTAUT Moderators

The UTAUT model, as previously mentioned, uses constructs correlated with moderators. As discussed in the literature review, Venkatesh (2003) in their seminal work defined the factors that affect PE, EE, SI, FC, to find Age, Gender, Experience, and Voluntariness of Use to be the moderating factors. For this study, the moderators have been identified as Age, Gender, Education and Income level. All 113 participants have answered these demographic questions, although, as discussed previously, there are data biases due to the reach and random sampling strategy, done to maximise the response rate. To identify the correlation between these moderators with the constructs of the baseline model, a set of hypotheses were tested using linear regression analysis. The hypothesis structure is presented in table 9.

Hypothesis No.	Null Hypothesis	Alternate Hypothesis
5	Gender does not have an impact on PE	Gender impacts PE
6	Age does not have an impact on PE	Age impacts PE
7	Age does not impact FC	Age impacts FC
8	Education level does not impact FC	Education level impacts FC
8	Gender does not impact EE	Gender impacts EE
10	Age does not impact EE	Age impacts EE
11	Gender does not impact SI	Gender impacts SI
12	Age does not impact SI	Age impacts SI
13	Education level does not impact SI	Education level impacts SI
14	Income level does not impact SI	Income level impacts SI
15	Gender does not impact Trust	Gender impacts Trust

16	Age does not impact Trust	Age impacts Trust
17	Education level does not impact Trust	Education level impacts Trust
18	Income level does not impact Trust	Income level impacts Trust
19	Education level does not impact EE	Education level impacts EE

*Table 9: Hypothesis construct for model moderators*

Through linear regression, the correlation and significance were evaluated between moderators and constructs. The following were the findings:

5. The p-value (0.931) for Gender → PE correlation, is not significant, null hypothesis is accepted; Gender does not have an impact on PE
6. The p-value (0.129) for Age → PE correlation is not significant, Null hypothesis is accepted; Age does not have an impact on PE.
7. The p-value (0.279) for Age → FC correlation is not significant, null hypothesis is accepted; Age does not have an impact on FC.
8. The p-value (0.86) for Education → FC correlation is not significant, null hypothesis is accepted; Education does not have an impact on FC.
9. The p-value (0.968) for Gender → EE correlation is not significant, null hypothesis is accepted; gender does not have an impact on EE.
10. The p-value (<0.001) for Age → EE correlation is considered as significant, alternate hypothesis is accepted; Age has an impact on EE. However, upon further inspection of the variable, individual significance of correlation is not significant, this combined with the high VIF values for some of the variables within EE may be contributing to this pattern. Potential multicollinearity may exist, or this may be linked to biased age data within the sample.
11. The p-value (0.791) for Gender → SI correlation is not significant, null hypothesis is accepted; Gender does not have an impact on SI.
12. The p-value (0.333) for Age → SI correlation is not significant, null hypothesis is accepted; Age does not have an impact on SI.
13. The p-value (0.448) for Education level → SI correlation is not significant, null hypothesis is accepted; Education level does not impact SI.

14. The p-value (0.358) for income level → SI correlation is not significant, null hypothesis is accepted; Income level does not have an impact on SI.
15. The p-value (0.791) for Gender → Trust correlation is not significant, null hypothesis is accepted; Gender does not have an impact on Trust.
16. The p-value (0.436) for Age → Trust correlation is not significant, null hypothesis is accepted; Age does not have an impact on Trust.
17. The p-value (0.381) for Education level → Trust correlation is not significant, null hypothesis is accepted; Education level does not have an impact on Trust.
18. The p-value (0.008) for Income level → Trust correlation is significant, alternate hypothesis is accepted; Income level has an impact on Trust, however, it must be noted that only the variable TLearn is contributing to this significance.
19. The p-value (0.39) for Education level → EE correlation is not significant, null hypothesis is accepted; Education level does not have an impact on EE.

By testing these hypotheses, the baseline model (fig.10), derived from the literature review and the original study presented by Gerlich (2023), the moderators and correlations have been simplified into a simpler UTAUT model (fig.19). The model graphically demonstrates the relationship between constructs identified, correlation evaluated through linear regression analysis, and through factor analysis. The factor loading between constructs and moderators have been gathered from component Matrixes produced during factor analysis (Appendix B 2-68). No correlation was found between age and other constructs, education as a moderator and constructs, therefore these moderators do not have any paths represented.

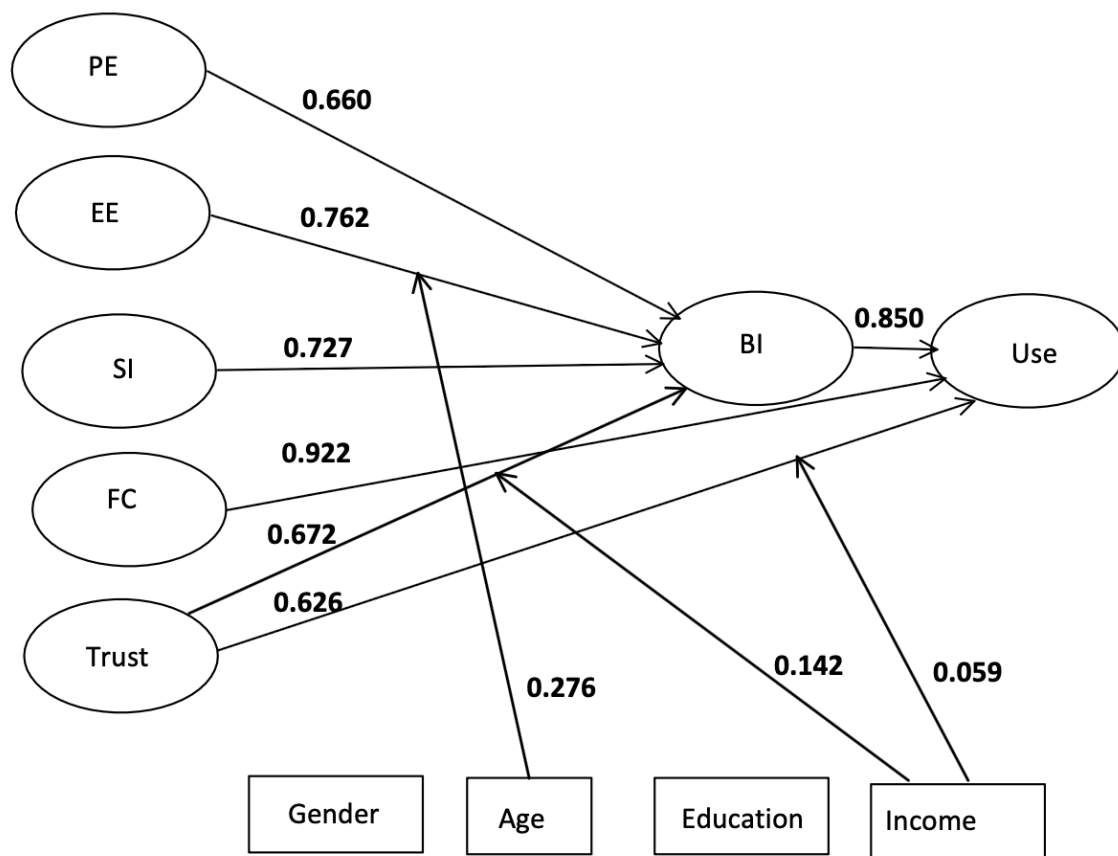


Figure 19: Simplified UTAUT model with relevant moderators, constructs, and factor loadings derived through quantitative analysis.

## 6. Discussion

The analysis performed on the survey responses, with the data set of 113 responses from professionals working within Ireland, was used to evaluate the factors that impact the attitude of people towards AI technology acceptance.

Descriptive statistical analysis revealed that the general attitude that people have towards AI technology is inclined towards positive, with a mean value of 4.63, which when compared to Gerlich's (2023) Global study of perception/attitude of people in countries including, USA, UK, China, Europe, using the same questionnaire, resulted in a positive inclination as well, with a value of 3.98.

Since this study was limited geographically, only to professional in Ireland, the factors impacting this overall positive attitude towards AI acceptance was evaluated, where cross-tabulation analysis demonstrated that Age and Gender did not have a significant impact on people's attitude towards AI technology acceptance, however,



there was a significant relationship identified between Education level and Income level.

According to Venkatesh (2003) Age, Gender, Experience, Voluntariness of use are the factors that impact Performance expectancy (PE), Effort expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioural intention (BI), and Actual use behaviour (Use), creating a comprehensive technology acceptance model, called unified theory of acceptance and use of technology. Researchers have found other factors impacting the technology acceptance and the general attitude amongst population towards acceptance of an innovation, these have led to modification and adaption of the originally proposed UTAUT model, Vorm (2022) argues “trust” to be a strong factor towards people’s perception and acceptance, Sheiktaheri (2024) uses UTAUT model to predict the behavioural intention and Use behaviour but by adding additional constructs and modifying the moderators to their participants and the environment, Ångström, (2023), identifies “Culture” as an important factor in people’s perception, Gerlich (2023) discussed factors of “Perceived risk” and “Cultural Bias” as important factors. Researchers have been utilizing various technology acceptance models and theories, however, UTAUT offers a comprehensive model to predict the technology acceptance behaviour intention and actual use, with approximately 70% accuracy (Mkhonto, Zuva, 2023; Mishra, Sharma, 2014; Venkatesh, et al., 2003). Gerlich (2023) found “Trust” to be an important factor in how people intend to use Artificial intelligence technology, and the actual use of artificial intelligence. This was proven further through factor analysis and linear regressions performed during the analysis, presented in the results and findings section above. There is a significant impact and correlation between trust and behavioural intention that people have, and how people are actually using AI technology, which is in line with Gerlich’s (2023), and Ångström’s (2023) study. To the contrary however, this study showed only “basic understanding of AI” (AI\_B\_Und) had a significant impact on the perception that AI is the future of mankind, among other variables that directly related to cultural beliefs impacting trust and overall attitude towards AI.

However, according to Venkatesh’s seminal work presented in 2003, the moderators (Age, Gender, Experience, Voluntariness of use) proposed were also proven to have an impact on the relationship between the constructs (PE, EE, FC, SI), Gerlich’s has modified the model to study the constructs with “country” as the moderators.

The factor analysis and linear regressions presented above have shown that the public perception factors, PE, SI, FC, and Trust, are not impacted by Age or Gender, which is not the same as the original UTAUT model (Venkatesh et al., 2003). Effort Expectancy was impacted by age; however, upon further inspection of the variable, individual significance of correlation is not significant, this combined with the high VIF values for some of the variables within EE may be contributing to this pattern.

Potential multicollinearity may exist, the sample size being biased for the variable “What is your age?” with a dominating 41.6% from the age group 35-44, which may have contributed to skewness of results.

It is seen through the rigorous testing on the survey data, that there is a correlation between the construct “trust” and moderator “Income level”. It is important to acknowledge that the sample data in this instance was biased with 52% of the participants income levels being “Under 50,000 Euro” in their survey responses. The descriptive statistical analysis reveals however, that on the total responses with trust levels at the negative end of the Likert scale (I completely disagree=1, mostly disagree=2), came from this group of responders, with 7.1% responding with “Completely disagree” and 3.5% responding with “Mostly disagree” to the questions contributing to their trust in the technology, other income level groups have either neutral (3 and 4 Likert scale values) or positive (5 and 6 Likert scale values) as their responses. Given only the “Under 50,000 Euro” has responded to negatively towards their trust in AI, it points to an underlying job security related insecurity. People with lower income level jobs would be employed in roles where decision-making power lies with managers and leaders, or work which may be automated in the coming years, as stated by researchers with AI’s capacity to learn and anticipated changes in the work force (Li, Bitterly, 2024; Raisch, Krakowski, 2021; Jankovic, Curovic, 2023; Sharma, Kumar, 2024; Unni, et al, 2023; Oyelunle, Boohene, 2024; Jorzik, et al., 2024). While the sample size is rather small, and consists certain biases, the analysis presents a picture where AI as a technology on its own is being accepted positively, however, the moderators originally proposed in the UTAUT models do not necessarily have an impact.

Through the analysis, Cross-Tabulation, linear regression, Factor analysis, and various validity tests such as KMO and Bartlett’s, Chi-Square, were performed, and pointed to Age and Gender not being a significant factor towards the attitude of people’s acceptance of AI technology. The simplified model (Fig. 20) presents the

model that may be used to study the perception/ attitudes, of people working within Ireland, towards AI technology, based on UTAUT model (Venkatesh, et al., 2003) and the global study performed by Gerlich (2023).

## 7. Conclusion

Artificial Intelligence is one of the most popular topics of research right now, not only in research, but also in our daily lives. Artificial intelligence (AI) was first introduced in the 1950s and by the 1960s was “effectively liquidated” due to the slow progress that was being made against what was expected (Raisch, Krakowski, 2021). While the literature has focussed on technical features, development, and benefits of AI with recent emphasis on the disadvantages of AI with job displacement, lack of emotional intelligence, ethicality and security (Raisch, Krakowski, 2021; Li,; Bitterly, 2024; Sharma, V.K.; Kumar, H., 2024), there’s a lack of research in how people are responding to AI technology in general. This research gap has been identified by Gerlich (2023) in their study of perceptions and attitude towards AI technology. While the global scale survey and analysis presented by Gerlich (2023) demonstrates the importance of studying these attitudes and the demographic factors that impact these perceptions, this paper acknowledges the need to study these factors and the overall perception at a more granular level, by limiting this to Ireland. The study aims to evaluate the attitude of professionals working within Ireland towards AI and the factors that impact the overall attitude among the population.

Technology adoption or acceptance is part of a larger life cycle of technology diffusion, as presented by Rogers in 1995, which is within the decision-making stage. Businesses and organisations around the world compete within a market to maintain a competitive edge, and technology must be adapted to maintain this competitive edge and sustain the business within a fiercely competitive environment. Artificial intelligence has the capacity to automate processes, to be more effective and efficient (Oyekunle, Boohene, 2024; Jorzik, P., et al, 2024). It cannot be denied that a technology is only successful if it is accepted and used by people. Only when the employees working within an organisation can use the technology aptly, will the organisation be able to maintain its competitive edge.

To predict this behaviour, various technology acceptance theories and models have been developed over the years, some are rooted strongly in the behavioural sciences, such as TPB, and TRA, while some are rather focussed on individual attitude and technical aspects, such as TTF and TAM. UTAUT is considered the most comprehensive and capable of predicting this behaviour so far, with approximately 70% accuracy (Mkhonto, Zuva, 2023; Sharma, Mishra, 2014; Williams, M., 2015), however, research using the UTAUT model has been dominated with only specific technological innovations being studied, and has been modified according to the innovation and the environment (Adji, 2024; Veronica, 2023; Sheikhtaheri, 2024), which leads the question as to whether the UTAUT model proposed by Venkatesh (2003) originally may not be valid as much as it did a decade ago. Venkatesh (2003) identified the need for a model that would be comprehensive enough for researchers to not have to sacrifice certain factors or create new models for technology acceptance study by having to study and pick the factors from other models, therefore, this study while being grounded in the UTAUT model, creates a baseline model specifically to be used to study the perceptions using factor analysis, linear regression, cross-tabulation, and validity and reliability tests such as the Chi-Square test, KMO and Bartlett's tests, ANOVA tests and coefficient/covariance tests using SPSS.

Through the literature review, "trust" was identified as a new construct that impacted both the behavioural intention and the actual use behaviour.

The online survey circulated among Irish professionals used snowball sampling method, and a sample size of 113 respondents was achieved. The results of the analysis showed that the general attitude towards AI technology was positive (mean value=4.63) while the impact of gender and age were insignificant on this attitude. Income and education level showed a significant impact on whether people believed that AI was the future of humankind. While the overall positive attitude was in line with Gerlich's (2023) global study of these perception, the original study did not particularly evaluate the impact of these demographic factors and focussed on the differences in terms of the country these respondents were from.

The factors that impacted the behavioural intention and actual use behaviour were identified through multiple linear regressions, to identify correlations and a factor analysis helped group questions together that would compute into each of the PE, EE, SI, FC and Trust variables.

The analysis revealed that PE, EE, SI, impacted only the BI, while “trust” impacted both BI and Use constructs (fig.20).

A valuable insight was discovered upon testing correlations between moderators (Age, Gender, education level, Income level) where gender did not have any impact at all on any of the constructs, Age only had some impact on EE, although this may be due to the data bias, since none of the variables within EE had a p-value  $<0.05$  to have a significant relationship, but a few of these variables did have a higher VIF value, as discussed above. Education did not seem to have any impact on these UTAUT constructs but income level did show a significant correlation on “trust”. This resulted in a simplified model that may be used for perception studies on a more local setting, presented in fig.20. It was seen that professionals with income level “under 50,000 EUR” were the only groups that had a negative response to trusting AI technology, which likely points to a fear of job displacement, or being replaced by AI. It must be noted that the group of respondents from the category income level “under 50,000 EURO” dominated the sample, with 52% of the overall responses coming from them, which may have led to this substantial outcome. Nevertheless, the relationship between income level and trust is significantly proven within the study and therefore creates an opportunity to be examined further.

The study was limited in terms of the small sample size with 113 participants, which might have caused skewed results, however, the KMO and Bartlett’s tests performed verify the reliability of the data used. Due to budgetary constraints, more accurate models such as AMOS, PLC, or SEM through CAGS could not be used, however, effort has been made through statistical testing using SPSS to check the validity and reliability of each test that is performed. While the research may not be conclusive to generalize, it strongly demonstrates a need for better technology acceptance models, suitable for this era or scale of technology, and that there is a need to evaluate the moderators proposed in the original UTAUT model, especially gender and age.

Future research in this domain should focus on a larger sample size to deduce the validity of a correlation between age, gender and the constructs. It is recommended that along with a larger sample size, AMOS, PLC, and SEM be used to more precisely estimate the factor loadings, correlation, and model fit. The impact of professional industry and job profile could also be studied to see if or how it might impact the public’s attitude.

In conclusion, there's a positive attitude among the professionals working within Ireland towards artificial intelligence technology acceptance, and the factors impacting the behavioural intention are the performance expectancy, effort expectancy, social influence, and trust, while the behavioural intention, facilitating conditions and trust constructs are the ones that impact actual use behaviour for AI technology adoption.

## 8. Reference List

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## Appendix A: Survey Questionnaire

The online survey questionnaire circulated amongst Irish professionals:

# AI technology adoption within Ireland and the impact of demographic factors

My name is Shreyashi Pal, I am a postgraduate student, seeking your anonymous participation in the survey, which is crucial to the academic research as part of my masters in management degree at NCI. The purpose of this research is to examine the correlation between demographic factors and the adoption of Artificial Intelligence technology, within Irish professional community and further contribute to the literature on AI technology adoption within Ireland.

Participants are requested to answer the questionnaire which is estimated to take an average of 10 minutes. Your response will be confidential, and all participants will remain anonymous. No information which may be used to identify you as an individual will be collected such as name, contact details or IP address. In analysing the data collected your response will be listed as “Participant #” ensuring full anonymity throughout the entire process. Your valuable contribution is essential to the success of this research, and I am extremely grateful for your participation.

The questionnaire intends to understand your familiarity and usage of AI technology in your professions, your outlook towards Artificial intelligence, and your opinion on AI as being beneficial or concerning. You will also be asked to select your age group, voluntary disclosure of your gender, educational background, and income range.

I thank you immensely for your time and participation.

1. What is your age? \*

- ☐ 18-24
- ☐ 25-34
- ☐ 35-44
- ☐ 45-54
- ☐ 55-64
- ☐ 65 and above

2. What is your gender?

- ☐ Woman
- ☐ Man
- ☐ Other

3. What is your highest education level? \*

- ☐ High school
- ☐ Bachelors
- ☐ Masters
- ☐ Doctorate

4. What is your income level? \*

- ☐ Under 50,000 Euro
- ☐ 50,000–100,000 Euro
- ☐ 100,000–150,000 Euro
- ☐ above 150,000 Euro

5. AI can increase efficiency and accuracy in tasks \*

- ☐ Completely Agree
- ☐ Mostly agree
- ☐ Slightly agree
- ☐ Slightly disagree
- ☐ Mostly Disagree
- ☐ Completely disagree

6. AI can offer convenience and save time. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely disagree

7. AI can improve decision-making processes \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

8. AI can help solve complex problems. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

9. AI can lead to cost savings \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

10. AI can create new job opportunities. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

11. Other benefit of AI I consider to be important for me:

12. AI may lead to job displacement. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree



13. AI may violate privacy concerns \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

14. AI may be used for malicious purposes. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

15. AI may cause errors and mistakes. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

16. AI may perpetuate bias and discrimination. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

17. AI may have unintended consequences. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

18. Other risks of AI I consider to be important for me:

19. I trust AI to perform tasks accurately. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

20. I trust AI to make reliable decisions. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

21. I believe AI is predictable. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

22. I have confidence in AI's ability to learn. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

23. I trust AI to keep my personal data secure. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

24. I trust AI to be used ethically. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

25. I trust an AI has less or no personal interests compared to humans. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

26. I trust AI because:

27. The government does not solve important issues like climate change. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

28. AI can help address societal issues such as climate change and social inequality. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree



29. Governments cannot solve global issues. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

30. AI has the potential to solve global issues \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

31. Politicians and countries have too many vested interests. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

32. AI has the potential to make society more equitable. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

33. AI can help create solutions to societal issues \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

34. I believe that AI can solve the following issue that humans failed to solve:

35. I use AI-powered products and services frequently. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

36. I have a basic understanding of what AI is and how it works. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

37. I have no experience with AI. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

38. I am comfortable using AI-powered products and services. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

39. I have encountered issues with AI-powered products and services in the past. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

40. My cultural background influences my attitudes towards AI. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

41. Different cultures may have different perceptions of AI. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

42. AI development should take cultural differences into account. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

43. My cultural beliefs impact my level of trust in AI. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

44. Cultural diversity can bring unique perspectives to the development and use of AI. \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree



45. I believe AI is the future for human kind \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

46. I believe AI is the end of Human Kind \*

- ☐ Completely Agree
- ☐ Mostly Agree
- ☐ Slightly Agree
- ☐ Slightly Disagree
- ☐ Mostly Disagree
- ☐ Completely Disagree

47. How optimistic or pessimistic are you about the future of AI and its impact on society?

---

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## Appendix B: Statistical Analysis

1. Factor analysis: Inconclusive due to different iterations and 3 additional latent factors that do not correlate with the original factor presented by Gerlich (2023). This is likely due to a different statistical model available under capacity and a higher sample size compared to the dataset used in this study.

**Rotated Component Matrix<sup>a</sup>**

	Component							
	1	2	3	4	5	6	7	8
Bias	<b>.914</b>							
UnintCons	<b>.903</b>							
Err	<b>.895</b>							
MalPurp	<b>.851</b>							
AIPriv	<b>.848</b>					<b>.378</b>		
Tethic	<b>.507</b>		<b>.391</b>	<b>.336</b>				<b>-.417</b>
TDataSec	<b>.496</b>		<b>.446</b>					<b>-.395</b>
FlunAccu		<b>.882</b>						
CompProb		<b>.882</b>						
Convnsavetime		<b>.865</b>						
DecMake		<b>.860</b>						
CostSav		<b>.801</b>						
NJobO		<b>.603</b>				<b>-.329</b>		
Alequit			<b>.934</b>					
AIGlobls			<b>.898</b>					
AI Soc Clim Chng			<b>.883</b>					
AI Soc lss			<b>.882</b>					
AI_B_Und				<b>.794</b>				
ComfAI		<b>.422</b>		<b>.708</b>				
AIProdUse				<b>.704</b>				
NoPers				<b>.688</b>				
AlfutMK		<b>.445</b>		<b>.505</b>				

CdifCons					.708	-.363		
CDif			.307		.675			
CdivAldev	-.331			.311	.660			
CAttAI			.462		.653			
Iss_AIprod	.514				-.597			
CTrstAI			.458		.584		.352	
PIInvest			-.327			.783		
GovGblbs						.753		
GovClimChng			-.305			.736		
JobDis						.610		
TAccu		.324					.730	
TPrecit					.327		.697	
TLearn		.355		.330			.624	
TRelDeci	.375	.350		.302			.434	
AlendMK								.721
No_AI			-.341	.360				.675

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.<sup>a</sup>

a. Rotation converged in 9 iterations.

## 2. Regression: PE/BI

### Descriptive Statistics

	Mean	Std. Deviation	N
AlfutMK	4.63	1.434	113
FlunAccu	5.28	.921	113
Convnsavetime	5.30	.905	113
DecMake	5.01	1.122	113
CompProb	5.10	.991	113
CostSav	4.82	1.167	113
NJobO	4.86	1.295	113

3.

### Correlations

		AlfutMK	FlunAccu	ConvnSavetime	DecMake	CompProb	CostSav	NJobO
Pearson Correlation	AlfutMK	1.000	.560	.465	.490	.547	.366	.486
	FlunAccu	.560	1.000	.893	.732	.831	.612	.566
	ConvnSavetime	.465	.893	1.000	.762	.803	.609	.486
	DecMake	.490	.732	.762	1.000	.794	.636	.517
	CompProb	.547	.831	.803	.794	1.000	.703	.596
	CostSav	.366	.612	.609	.636	.703	1.000	.492
	NJobO	.486	.566	.486	.517	.596	.492	1.000
Sig. (1-tailed)	AlfutMK	.	<.001	<.001	<.001	<.001	<.001	<.001
	FlunAccu	.000	.	.000	.000	.000	.000	.000
	ConvnSavetime	.000	.000	.	.000	.000	.000	.000
	DecMake	.000	.000	.000	.	.000	.000	.000
	CompProb	.000	.000	.000	.000	.	.000	.000
	CostSav	.000	.000	.000	.000	.000	.	.000
	NJobO	.000	.000	.000	.000	.000	.000	.
N	AlfutMK	113	113	113	113	113	113	113
	FlunAccu	113	113	113	113	113	113	113
	ConvnSavetime	113	113	113	113	113	113	113
	DecMake	113	113	113	113	113	113	113
	CompProb	113	113	113	113	113	113	113
	CostSav	113	113	113	113	113	113	113
	NJobO	113	113	113	113	113	113	113

4.

### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	NJobO, ConvnSavetime, CostSav, DecMake, CompProb, FlunAccu <sup>b</sup>	.	Enter

a. Dependent Variable: AlfutMK

b. All requested variables entered.

5.

### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	<b>.619<sup>a</sup></b>	<b>.384</b>	<b>.349</b>	<b>1.157</b>	<b>.384</b>	<b>10.999</b>	<b>6</b>	<b>106</b>	<b>&lt;.001</b>

a. Predictors: (Constant), NJobO, ConvnSavetime, CostSav, DecMake, CompProb, FlunAccu

b. Dependent Variable: AlfutMK

6.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>88.398</b>	<b>6</b>	<b>14.733</b>	<b>10.999</b>	<b>&lt;.001<sup>b</sup></b>
	Residual	<b>141.992</b>	<b>106</b>	<b>1.340</b>		
	Total	<b>230.389</b>	<b>112</b>			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), NJobO, ConvnSavetime, CostSav, DecMake, CompProb, FlunAccu

7.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>.066</b>	<b>.669</b>		<b>.099</b>	<b>.921</b>	<b>-1.260</b>	<b>1.392</b>
	FlunAccu	<b>.726</b>	<b>.298</b>	<b>.466</b>	<b>2.435</b>	<b>.017</b>	<b>.135</b>	<b>1.317</b>
	Convnsavetime	<b>-.425</b>	<b>.292</b>	<b>-.268</b>	<b>-1.455</b>	<b>.149</b>	<b>-1.004</b>	<b>.154</b>
	DecMake	<b>.185</b>	<b>.174</b>	<b>.145</b>	<b>1.067</b>	<b>.289</b>	<b>-.159</b>	<b>.529</b>
	CompProb	<b>.296</b>	<b>.246</b>	<b>.205</b>	<b>1.205</b>	<b>.231</b>	<b>-.191</b>	<b>.784</b>
	CostSav	<b>-.111</b>	<b>.135</b>	<b>-.091</b>	<b>-.825</b>	<b>.411</b>	<b>-.379</b>	<b>.156</b>
	NJobO	<b>.222</b>	<b>.109</b>	<b>.200</b>	<b>2.043</b>	<b>.044</b>	<b>.007</b>	<b>.437</b>

a. Dependent Variable: AlfutMK

8.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>.96</b>	<b>5.85</b>	<b>4.63</b>	<b>.888</b>	<b>113</b>
Std. Predicted Value	<b>-4.130</b>	<b>1.375</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.130</b>	<b>.626</b>	<b>.258</b>	<b>.129</b>	<b>113</b>

Adjusted Predicted Value	.95	5.86	4.63	.913	113
Residual	-3.533	3.815	.000	1.126	113
Std. Residual	-3.052	3.296	.000	.973	113
Stud. Residual	-3.257	3.605	.001	1.019	113
Deleted Residual	-4.023	4.564	.001	1.239	113
Stud. Deleted Residual	-3.417	3.831	-.001	1.038	113
Mahal. Distance	.429	31.812	5.947	7.231	113
Cook's Distance	.000	.364	.015	.045	113
Centered Leverage Value	.004	.284	.053	.065	113

a. Dependent Variable: AlfutMK

## 9. Regression: PE/Actual use behaviour (Not really impacting as such the actual use with this construct PE)

### Descriptive Statistics

	Mean	Std. Deviation	N
AIProdUse	4.65	1.195	113
FlunAccu	5.28	.921	113
Convnsavetime	5.30	.905	113
DecMake	5.01	1.122	113
CompProb	5.10	.991	113
CostSav	4.82	1.167	113
NJobO	4.86	1.295	113

10.

### Correlations

		AIProdUse	FlunAccu	Convnsavetime	DecMake	CompProb	CostSav	NJobO
Pearson Correlation	AIProdUse	1.000	.352	.380	.415	.429	.326	.354
	FlunAccu	.352	1.000	.893	.732	.831	.612	.566
	Convnsavetime	.380	.893	1.000	.762	.803	.609	.486
	DecMake	.415	.732	.762	1.000	.794	.636	.517
	CompProb	.429	.831	.803	.794	1.000	.703	.596
	CostSav	.326	.612	.609	.636	.703	1.000	.492

Sig. (1-tailed)	NJobO	.354	.566	.486	.517	.596	.492	1.000
	AIProdUse	.	<.001	<.001	<.001	<.001	<.001	<.001
	FlunAccu	.000	.	.000	.000	.000	.000	.000
	ConvsnSavetime	.000	.000	.	.000	.000	.000	.000
	DecMake	.000	.000	.000	.	.000	.000	.000
	CompProb	.000	.000	.000	.000	.	.000	.000
	CostSav	.000	.000	.000	.000	.000	.	.000
	NJobO	.000	.000	.000	.000	.000	.000	.
	AIProdUse	113	113	113	113	113	113	113
	FlunAccu	113	113	113	113	113	113	113
	ConvsnSavetime	113	113	113	113	113	113	113
	DecMake	113	113	113	113	113	113	113
	CompProb	113	113	113	113	113	113	113
	CostSav	113	113	113	113	113	113	113
	NJobO	113	113	113	113	113	113	113

11.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	NJobO, ConvsnSavetime, CostSav, DecMake, CompProb, FlunAccu <sup>b</sup>	.	Enter

a. Dependent Variable: AIProdUse

b. All requested variables entered.

12.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	.469 <sup>a</sup>	.220	.176	1.084	.220	4.985	6	106	<.001

a. Predictors: (Constant), NJobO, ConvsnSavetime, CostSav, DecMake, CompProb, FlunAccu

b. Dependent Variable: AIProdUse

13.

#### ANOVA<sup>a</sup>



Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>35.178</b>	<b>6</b>	<b>5.863</b>	<b>4.985</b>	<b>&lt;.001<sup>b</sup></b>
	Residual	<b>124.662</b>	<b>106</b>	<b>1.176</b>		
	Total	<b>159.841</b>	<b>112</b>			

a. Dependent Variable: AIProdUse

b. Predictors: (Constant), NJobO, ConvnSavetime, CostSav, DecMake, CompProb, FlunAccu

14.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>1.819</b>	<b>.627</b>		<b>2.903</b>	<b>.005</b>	<b>.577</b>	<b>3.062</b>
	FlunAccu	<b>-.290</b>	<b>.279</b>	<b>-.223</b>	<b>-1.038</b>	<b>.302</b>	<b>-.844</b>	<b>.264</b>
	Convnsavetime	<b>.238</b>	<b>.274</b>	<b>.181</b>	<b>.871</b>	<b>.386</b>	<b>-.304</b>	<b>.781</b>
	DecMake	<b>.177</b>	<b>.163</b>	<b>.166</b>	<b>1.086</b>	<b>.280</b>	<b>-.146</b>	<b>.499</b>
	CompProb	<b>.293</b>	<b>.230</b>	<b>.243</b>	<b>1.271</b>	<b>.207</b>	<b>-.164</b>	<b>.750</b>
	CostSav	<b>-.004</b>	<b>.126</b>	<b>-.004</b>	<b>-.029</b>	<b>.977</b>	<b>-.254</b>	<b>.247</b>
	NJobO	<b>.151</b>	<b>.102</b>	<b>.164</b>	<b>1.487</b>	<b>.140</b>	<b>-.050</b>	<b>.353</b>

a. Dependent Variable: AIProdUse

15.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>2.38</b>	<b>5.51</b>	<b>4.65</b>	<b>.560</b>	<b>113</b>
Std. Predicted Value	<b>-4.034</b>	<b>1.535</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.122</b>	<b>.587</b>	<b>.242</b>	<b>.121</b>	<b>113</b>
Adjusted Predicted Value	<b>2.71</b>	<b>5.45</b>	<b>4.65</b>	<b>.564</b>	<b>113</b>
Residual	<b>-4.213</b>	<b>2.750</b>	<b>.000</b>	<b>1.055</b>	<b>113</b>
Std. Residual	<b>-3.885</b>	<b>2.536</b>	<b>.000</b>	<b>.973</b>	<b>113</b>
Stud. Residual	<b>-3.924</b>	<b>2.774</b>	<b>-.002</b>	<b>1.010</b>	<b>113</b>
Deleted Residual	<b>-4.332</b>	<b>3.290</b>	<b>-.005</b>	<b>1.139</b>	<b>113</b>
Stud. Deleted Residual	<b>-4.224</b>	<b>2.867</b>	<b>-.010</b>	<b>1.044</b>	<b>113</b>
Mahal. Distance	<b>.429</b>	<b>31.812</b>	<b>5.947</b>	<b>7.231</b>	<b>113</b>

Cook's Distance	<b>.000</b>	<b>.216</b>	<b>.012</b>	<b>.032</b>	<b>113</b>
Centered Leverage Value	<b>.004</b>	<b>.284</b>	<b>.053</b>	<b>.065</b>	<b>113</b>

a. Dependent Variable: AIProdUse

## 16. Regression: FC/BI

### Descriptive Statistics

	Mean	Std. Deviation	N
AlfutMK	<b>4.63</b>	<b>1.434</b>	<b>113</b>
Tethic	<b>3.53</b>	<b>1.685</b>	<b>113</b>
AlSocClimChn	<b>3.04</b>	<b>1.655</b>	<b>113</b>
g			
AlGlobls	<b>2.88</b>	<b>1.748</b>	<b>113</b>
AlSoclss	<b>3.26</b>	<b>1.715</b>	<b>113</b>

17.

### Correlations

		AlfutMK	Tethic	AlSocClimChn	AlGlobls	AlSoclss
Pearson Correlation	AlfutMK	<b>1.000</b>	<b>.119</b>	<b>.082</b>	<b>.192</b>	<b>.148</b>
	Tethic	<b>.119</b>	<b>1.000</b>	<b>.475</b>	<b>.456</b>	<b>.422</b>
	AlSocClimChn	<b>.082</b>	<b>.475</b>	<b>1.000</b>	<b>.903</b>	<b>.814</b>
	g					
	AlGlobls	<b>.192</b>	<b>.456</b>	<b>.903</b>	<b>1.000</b>	<b>.835</b>
	AlSoclss	<b>.148</b>	<b>.422</b>	<b>.814</b>	<b>.835</b>	<b>1.000</b>
Sig. (1-tailed)	AlfutMK	.	<b>.104</b>	<b>.193</b>	<b>.021</b>	<b>.059</b>
	Tethic	<b>.104</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	AlSocClimChn	<b>.193</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>
	g					
	AlGlobls	<b>.021</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>
	AlSoclss	<b>.059</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.
N	AlfutMK	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Tethic	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AlSocClimChn	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	g					
	AlGlobls	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AlSoclss	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

	AlSoclss	113	113	113	113	113
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18.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	AlSoclss, Tethic, AlSocClimChng, AlGlobls <sup>b</sup>		Enter

a. Dependent Variable: AlfutMK

b. All requested variables entered.

19.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	.296 <sup>a</sup>	.087	.054	1.395	.087	2.585	4	108	.041

a. Predictors: (Constant), AlSoclss, Tethic, AlSocClimChng, AlGlobls

b. Dependent Variable: AlfutMK

20.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20.127	4	5.032	2.585	.041 <sup>b</sup>
	Residual	210.262	108	1.947		
	Total	230.389	112			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), AlSoclss, Tethic, AlSocClimChng, AlGlobls

21.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	4.253	.344		12.347	<.001	3.570	4.935
	Tethic	.068	.089	.080	.767	.445	-.108	.245
	AlSocClimChng	-.465	.194	-.537	-2.402	.018	-.849	-.081

	AlGlobls	.488	.192	.594	2.539	.013	.107	.868
	AlSoclss	.045	.145	.054	.315	.754	-.241	.332

a. Dependent Variable: AlfutMK

22.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.04	6.19	4.63	.424	113
Std. Predicted Value	-3.751	3.690	.000	1.000	113
Standard Error of Predicted Value	.149	.640	.276	.101	113
Adjusted Predicted Value	3.26	6.24	4.63	.416	113
Residual	-3.798	2.076	.000	1.370	113
Std. Residual	-2.722	1.488	.000	.982	113
Stud. Residual	-2.739	1.525	-.001	1.004	113
Deleted Residual	-3.847	2.179	-.003	1.434	113
Stud. Deleted Residual	-2.827	1.534	-.006	1.016	113
Mahal. Distance	.283	22.567	3.965	4.196	113
Cook's Distance	.000	.166	.010	.021	113
Centered Leverage Value	.003	.201	.035	.037	113

a. Dependent Variable: AlfutMK

### 23. Regression: FC/UB (Definitely a correlation)

#### Descriptive Statistics

	Mean	Std. Deviation	N
AlProdUse	4.65	1.195	113
Tethic	3.53	1.685	113
AlSocClimChn g	3.04	1.655	113
AlGlobls	2.88	1.748	113
AlSoclss	3.26	1.715	113

24.

#### Correlations

		AIProdUse	Tethic	AI SocClimCh ng	AI Globls	AI Soclss
Pearson Correlation	AIProdUse	<b>1.000</b>	<b>.249</b>	<b>.103</b>	<b>.120</b>	<b>.006</b>
	Tethic	<b>.249</b>	<b>1.000</b>	<b>.475</b>	<b>.456</b>	<b>.422</b>
	AI SocClimChn g	<b>.103</b>	<b>.475</b>	<b>1.000</b>	<b>.903</b>	<b>.814</b>
	AI Globls	<b>.120</b>	<b>.456</b>	<b>.903</b>	<b>1.000</b>	<b>.835</b>
	AI Soclss	<b>.006</b>	<b>.422</b>	<b>.814</b>	<b>.835</b>	<b>1.000</b>
Sig. (1-tailed)	AIProdUse	.	<b>.004</b>	<b>.139</b>	<b>.103</b>	<b>.477</b>
	Tethic	<b>.004</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	AI SocClimChn g	<b>.139</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>
	AI Globls	<b>.103</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>
	AI Soclss	<b>.477</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.
N	AIProdUse	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Tethic	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AI SocClimChn g	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AI Globls	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AI Soclss	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

25.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	<b>AI Soclss, Tethic, AI SocClimC hng, AI Globls<sup>b</sup></b>	.	<b>Enter</b>

a. Dependent Variable: AIProdUse

b. All requested variables entered.

26.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	<b>.314<sup>a</sup></b>	<b>.099</b>	<b>.065</b>	<b>1.155</b>	<b>.099</b>	<b>2.961</b>	<b>4</b>	<b>108</b>	<b>.023</b>

a. Predictors: (Constant), AISoclss, Tethic, AISocClimChng, AIGlobls

b. Dependent Variable: AIProdUse

27.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>15.798</b>	<b>4</b>	<b>3.950</b>	<b>2.961</b>	<b>.023<sup>b</sup></b>
	Residual	<b>144.042</b>	<b>108</b>	<b>1.334</b>		
	Total	<b>159.841</b>	<b>112</b>			

a. Dependent Variable: AIProdUse

b. Predictors: (Constant), AISoclss, Tethic, AISocClimChng, AIGlobls

28.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>4.207</b>	<b>.285</b>		<b>14.756</b>	<b>&lt;.001</b>	<b>3.642</b>	<b>4.772</b>
	Tethic	<b>.187</b>	<b>.074</b>	<b>.264</b>	<b>2.539</b>	<b>.013</b>	<b>.041</b>	<b>.334</b>
	AISocClimChng	<b>-.006</b>	<b>.160</b>	<b>-.009</b>	<b>-.038</b>	<b>.970</b>	<b>-.324</b>	<b>.312</b>
	AIGlobls	<b>.203</b>	<b>.159</b>	<b>.297</b>	<b>1.279</b>	<b>.204</b>	<b>-.112</b>	<b>.518</b>
	AISoclss	<b>-.242</b>	<b>.120</b>	<b>-.348</b>	<b>-2.023</b>	<b>.046</b>	<b>-.479</b>	<b>-.005</b>

a. Dependent Variable: AIProdUse

29.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>3.32</b>	<b>5.29</b>	<b>4.65</b>	<b>.376</b>	<b>113</b>
Std. Predicted Value	<b>-3.531</b>	<b>1.705</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.123</b>	<b>.530</b>	<b>.228</b>	<b>.084</b>	<b>113</b>
Adjusted Predicted Value	<b>3.41</b>	<b>5.42</b>	<b>4.66</b>	<b>.386</b>	<b>113</b>
Residual	<b>-3.874</b>	<b>1.850</b>	<b>.000</b>	<b>1.134</b>	<b>113</b>
Std. Residual	<b>-3.355</b>	<b>1.602</b>	<b>.000</b>	<b>.982</b>	<b>113</b>
Stud. Residual	<b>-3.422</b>	<b>1.637</b>	<b>-.004</b>	<b>1.017</b>	<b>113</b>
Deleted Residual	<b>-4.148</b>	<b>1.931</b>	<b>-.010</b>	<b>1.219</b>	<b>113</b>
Stud. Deleted Residual	<b>-3.607</b>	<b>1.650</b>	<b>-.011</b>	<b>1.037</b>	<b>113</b>

Mahal. Distance	<b>.283</b>	<b>22.567</b>	<b>3.965</b>	<b>4.196</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.509</b>	<b>.016</b>	<b>.054</b>	<b>113</b>
Centered Leverage Value	<b>.003</b>	<b>.201</b>	<b>.035</b>	<b>.037</b>	<b>113</b>

a. Dependent Variable: AIProdUse

### 30. Regression: EE/UB Significant correlation

#### Descriptive Statistics

	Mean	Std. Deviation	N
AIProdUse	<b>4.65</b>	<b>1.195</b>	<b>113</b>
NoPers	<b>4.74</b>	<b>1.361</b>	<b>113</b>
AI_B_Und	<b>4.81</b>	<b>1.076</b>	<b>113</b>
ComfAI	<b>4.68</b>	<b>1.112</b>	<b>113</b>

#### Correlations

		AIProdUse	NoPers	AI_B_Und	ComfAI
Pearson Correlation	AIProdUse	<b>1.000</b>	<b>.366</b>	<b>.647</b>	<b>.627</b>
	NoPers	<b>.366</b>	<b>1.000</b>	<b>.459</b>	<b>.429</b>
	AI_B_Und	<b>.647</b>	<b>.459</b>	<b>1.000</b>	<b>.753</b>
	ComfAI	<b>.627</b>	<b>.429</b>	<b>.753</b>	<b>1.000</b>
Sig. (1-tailed)	AIProdUse	<b>.</b>	<b>&lt;.001</b>	<b>&lt;.001</b>	<b>&lt;.001</b>
	NoPers	<b>.000</b>	<b>.</b>	<b>.000</b>	<b>.000</b>
	AI_B_Und	<b>.000</b>	<b>.000</b>	<b>.</b>	<b>.000</b>
	ComfAI	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.</b>
N	AIProdUse	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	NoPers	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	AI_B_Und	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	ComfAI	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

31.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
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1	ComfAI, NoPers, AI_B_Und <sup>b</sup>	. Enter
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a. Dependent Variable: AIProdUse

b. All requested variables entered.

32.

**Model Summary<sup>b</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	.683 <sup>a</sup>	.466	.451	.885	.466	31.714	3	109	<.001

a. Predictors: (Constant), ComfAI, NoPers, AI\_B\_Und

b. Dependent Variable: AIProdUse

33.

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74.496	3	24.832	31.714	<.001 <sup>b</sup>
	Residual	85.345	109	.783		
	Total	159.841	112			

a. Dependent Variable: AIProdUse

b. Predictors: (Constant), ComfAI, NoPers, AI\_B\_Und

34.

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.785	.415		1.890	.061	-.038	1.608
	NoPers	.048	.070	.055	.689	.492	-.090	.187
	AI_B_Und	.431	.121	.388	3.548	<.001	.190	.671
	ComfAI	.334	.116	.311	2.892	.005	.105	.563

a. Dependent Variable: AIProdUse

35.

**Residuals Statistics<sup>a</sup>**

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.60	5.66	4.65	.816	113



Std. Predicted Value	<b>-3.738</b>	<b>1.245</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.087</b>	<b>.407</b>	<b>.152</b>	<b>.069</b>	<b>113</b>
Adjusted Predicted Value	<b>1.70</b>	<b>5.97</b>	<b>4.65</b>	<b>.818</b>	<b>113</b>
Residual	<b>-4.469</b>	<b>2.202</b>	<b>.000</b>	<b>.873</b>	<b>113</b>
Std. Residual	<b>-5.050</b>	<b>2.488</b>	<b>.000</b>	<b>.987</b>	<b>113</b>
Stud. Residual	<b>-5.323</b>	<b>2.688</b>	<b>.000</b>	<b>1.021</b>	<b>113</b>
Deleted Residual	<b>-4.965</b>	<b>2.570</b>	<b>.000</b>	<b>.937</b>	<b>113</b>
Stud. Deleted Residual	<b>-6.160</b>	<b>2.769</b>	<b>-.014</b>	<b>1.092</b>	<b>113</b>
Mahal. Distance	<b>.092</b>	<b>22.698</b>	<b>2.973</b>	<b>4.193</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.787</b>	<b>.019</b>	<b>.083</b>	<b>113</b>
Centered Leverage Value	<b>.001</b>	<b>.203</b>	<b>.027</b>	<b>.037</b>	<b>113</b>

a. Dependent Variable: AIProdUse

### 36. Regression: EE/BI

#### Descriptive Statistics

	Mean	Std. Deviation	N
AlfutMK	<b>4.63</b>	<b>1.434</b>	<b>113</b>
NoPers	<b>4.74</b>	<b>1.361</b>	<b>113</b>
AI_B_Und	<b>4.81</b>	<b>1.076</b>	<b>113</b>
ComfAI	<b>4.68</b>	<b>1.112</b>	<b>113</b>

37.

#### Correlations

		AlfutMK	NoPers	AI_B_Und	ComfAI
Pearson Correlation	AlfutMK	<b>1.000</b>	<b>.271</b>	<b>.629</b>	<b>.541</b>
	NoPers	<b>.271</b>	<b>1.000</b>	<b>.459</b>	<b>.429</b>
	AI_B_Und	<b>.629</b>	<b>.459</b>	<b>1.000</b>	<b>.753</b>
	ComfAI	<b>.541</b>	<b>.429</b>	<b>.753</b>	<b>1.000</b>
Sig. (1-tailed)	AlfutMK	<b>.</b>	<b>.002</b>	<b>&lt;.001</b>	<b>&lt;.001</b>
	NoPers	<b>.002</b>	<b>.</b>	<b>.000</b>	<b>.000</b>
	AI_B_Und	<b>.000</b>	<b>.000</b>	<b>.</b>	<b>.000</b>
	ComfAI	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.</b>
N	AlfutMK	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

	NoPers	113	113	113	113
	AI_B_Und	113	113	113	113
	ComfAI	113	113	113	113

38.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	ComfAI, NoPers, AI_B_Und <sup>b</sup>		Enter

a. Dependent Variable: AlfutMK

b. All requested variables entered.

39.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	.639 <sup>a</sup>	.408	.391	1.119	.408	25.016	3	109	<.001

a. Predictors: (Constant), ComfAI, NoPers, AI\_B\_Und

b. Dependent Variable: AlfutMK

40.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	93.944	3	31.315	25.016	<.001 <sup>b</sup>
	Residual	136.445	109	1.252		
	Total	230.389	112			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), ComfAI, NoPers, AI\_B\_Und

41.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.484	.525		.921	.359	-.557	1.524
	NoPers	-.042	.088	-.040	-.479	.633	-.217	.133
	AI_B_Und	.701	.153	.526	4.569	<.001	.397	1.005

	ComfAl	.209	.146	.162	1.428	.156	-.081	.498
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a. Dependent Variable: AlfutMK

42.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1.14	5.86	4.63	.916	113
Std. Predicted Value	-3.810	1.342	.000	1.000	113
Standard Error of Predicted Value	.110	.515	.192	.087	113
Adjusted Predicted Value	1.18	5.84	4.62	.915	113
Residual	-4.479	1.957	.000	1.104	113
Std. Residual	-4.003	1.749	.000	.987	113
Stud. Residual	-4.063	1.781	.002	1.006	113
Deleted Residual	-4.614	2.117	.004	1.147	113
Stud. Deleted Residual	-4.391	1.799	-.005	1.030	113
Mahal. Distance	.092	22.698	2.973	4.193	113
Cook's Distance	.000	.132	.010	.023	113
Centered Leverage Value	.001	.203	.027	.037	113

a. Dependent Variable: AlfutMK

#### 43. Regression: SI/BI

##### Descriptive Statistics

	Mean	Std. Deviation	N
AlfutMK	4.63	1.434	113
TPrecit	3.98	1.414	113
Iss_Alprod	3.23	1.587	113
CAttAl	3.48	1.452	113
CDif	3.96	1.378	113
CdifCons	3.88	1.591	113
CTrstAl	3.39	1.503	113

44.

##### Correlations

		AlfutMK	TPrecit	Iss_Alprod	CAttAI	CDif	CdifCons	CTrstAI
Pearson Correlation	AlfutMK	<b>1.000</b>	<b>.146</b>	<b>-.146</b>	<b>.060</b>	<b>.100</b>	<b>.130</b>	<b>.076</b>
	TPrecit	<b>.146</b>	<b>1.000</b>	<b>-.388</b>	<b>.361</b>	<b>.297</b>	<b>.059</b>	<b>.285</b>
	Iss_Alprod	<b>-.146</b>	<b>-.388</b>	<b>1.000</b>	<b>-.439</b>	<b>-.416</b>	<b>-.449</b>	<b>-.263</b>
	CAttAI	<b>.060</b>	<b>.361</b>	<b>-.439</b>	<b>1.000</b>	<b>.666</b>	<b>.418</b>	<b>.704</b>
	CDif	<b>.100</b>	<b>.297</b>	<b>-.416</b>	<b>.666</b>	<b>1.000</b>	<b>.588</b>	<b>.664</b>
	CdifCons	<b>.130</b>	<b>.059</b>	<b>-.449</b>	<b>.418</b>	<b>.588</b>	<b>1.000</b>	<b>.448</b>
	CTrstAI	<b>.076</b>	<b>.285</b>	<b>-.263</b>	<b>.704</b>	<b>.664</b>	<b>.448</b>	<b>1.000</b>
Sig. (1-tailed)	AlfutMK	.	<b>.061</b>	<b>.061</b>	<b>.263</b>	<b>.146</b>	<b>.085</b>	<b>.212</b>
	TPrecit	<b>.061</b>	.	<b>.000</b>	<b>.000</b>	<b>.001</b>	<b>.269</b>	<b>.001</b>
	Iss_Alprod	<b>.061</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.002</b>
	CAttAI	<b>.263</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	CDif	<b>.146</b>	<b>.001</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>
	CdifCons	<b>.085</b>	<b>.269</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>
	CTrstAI	<b>.212</b>	<b>.001</b>	<b>.002</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.
N	AlfutMK	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TPrecit	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Iss_Alprod	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CAttAI	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CDif	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CdifCons	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CTrstAI	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

45.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	<b>CTrstAI, Iss_Alprod, TPrecit, CdifCons, CAttAI, CDif<sup>b</sup></b>	.	<b>Enter</b>

a. Dependent Variable: AlfutMK

b. All requested variables entered.

46.

#### Model Summary<sup>b</sup>

Model	R	R Square			Change Statistics
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			Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	<b>.205<sup>a</sup></b>	<b>.042</b>	<b>-.012</b>	<b>1.443</b>	<b>.042</b>	<b>.777</b>	<b>6</b>	<b>106</b>	<b>.589</b>

a. Predictors: (Constant), CTrstAI, Iss\_Alprod, TPrecit, CdifCons, CAttAI, CDif

b. Dependent Variable: AlfutMK

47.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>9.710</b>	<b>6</b>	<b>1.618</b>	<b>.777</b>	<b>.589<sup>b</sup></b>
	Residual	<b>220.679</b>	<b>106</b>	<b>2.082</b>		
	Total	<b>230.389</b>	<b>112</b>			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), CTrstAI, Iss\_Alprod, TPrecit, CdifCons, CAttAI, CDif

48.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>4.120</b>	<b>.898</b>		<b>4.588</b>	<b>&lt;.001</b>	<b>2.339</b>	<b>5.900</b>
	TPrecit	<b>.135</b>	<b>.112</b>	<b>.134</b>	<b>1.211</b>	<b>.228</b>	<b>-.086</b>	<b>.357</b>
	Iss_Alprod	<b>-.068</b>	<b>.110</b>	<b>-.075</b>	<b>-.622</b>	<b>.535</b>	<b>-.285</b>	<b>.149</b>
	CAttAI	<b>-.090</b>	<b>.150</b>	<b>-.092</b>	<b>-.603</b>	<b>.548</b>	<b>-.388</b>	<b>.207</b>
	CDif	<b>.006</b>	<b>.158</b>	<b>.006</b>	<b>.038</b>	<b>.970</b>	<b>-.307</b>	<b>.319</b>
	CdifCons	<b>.099</b>	<b>.116</b>	<b>.110</b>	<b>.855</b>	<b>.394</b>	<b>-.130</b>	<b>.328</b>
	CTrstAI	<b>.028</b>	<b>.141</b>	<b>.030</b>	<b>.200</b>	<b>.842</b>	<b>-.251</b>	<b>.308</b>

a. Dependent Variable: AlfutMK

49.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>3.89</b>	<b>5.36</b>	<b>4.63</b>	<b>.294</b>	<b>113</b>
Std. Predicted Value	<b>-2.511</b>	<b>2.497</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.158</b>	<b>.783</b>	<b>.337</b>	<b>.124</b>	<b>113</b>
Adjusted Predicted Value	<b>3.71</b>	<b>5.77</b>	<b>4.63</b>	<b>.371</b>	<b>113</b>
Residual	<b>-3.961</b>	<b>2.111</b>	<b>.000</b>	<b>1.404</b>	<b>113</b>

Std. Residual	<b>-2.745</b>	<b>1.463</b>	<b>.000</b>	<b>.973</b>	<b>113</b>
Stud. Residual	<b>-2.933</b>	<b>1.525</b>	<b>-.001</b>	<b>1.026</b>	<b>113</b>
Deleted Residual	<b>-4.773</b>	<b>2.292</b>	<b>-.004</b>	<b>1.569</b>	<b>113</b>
Stud. Deleted Residual	<b>-3.045</b>	<b>1.534</b>	<b>-.007</b>	<b>1.042</b>	<b>113</b>
Mahal. Distance	<b>.354</b>	<b>32.017</b>	<b>5.947</b>	<b>5.825</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.438</b>	<b>.018</b>	<b>.062</b>	<b>113</b>
Centered Leverage Value	<b>.003</b>	<b>.286</b>	<b>.053</b>	<b>.052</b>	<b>113</b>

a. Dependent Variable: AlfutMK

## 50. Regression: SI/Actual Use Behaviour

### Descriptive Statistics

	Mean	Std. Deviation	N
AlProdUse	<b>4.65</b>	<b>1.195</b>	<b>113</b>
TPrecit	<b>3.98</b>	<b>1.414</b>	<b>113</b>
Iss_Alprod	<b>3.23</b>	<b>1.587</b>	<b>113</b>
CAttAI	<b>3.48</b>	<b>1.452</b>	<b>113</b>
CDif	<b>3.96</b>	<b>1.378</b>	<b>113</b>
CdifCons	<b>3.88</b>	<b>1.591</b>	<b>113</b>
CTrstAI	<b>3.39</b>	<b>1.503</b>	<b>113</b>

51.

### Correlations

		AlProdUse	TPrecit	Iss_Alprod	CAttAI	CDif	CdifCons	CTrstAI
Pearson Correlation	AlProdUse	<b>1.000</b>	<b>.255</b>	<b>-.131</b>	<b>.129</b>	<b>.099</b>	<b>.162</b>	<b>.058</b>
	TPrecit	<b>.255</b>	<b>1.000</b>	<b>-.388</b>	<b>.361</b>	<b>.297</b>	<b>.059</b>	<b>.285</b>
	Iss_Alprod	<b>-.131</b>	<b>-.388</b>	<b>1.000</b>	<b>-.439</b>	<b>-.416</b>	<b>-.449</b>	<b>-.263</b>
	CAttAI	<b>.129</b>	<b>.361</b>	<b>-.439</b>	<b>1.000</b>	<b>.666</b>	<b>.418</b>	<b>.704</b>
	CDif	<b>.099</b>	<b>.297</b>	<b>-.416</b>	<b>.666</b>	<b>1.000</b>	<b>.588</b>	<b>.664</b>
	CdifCons	<b>.162</b>	<b>.059</b>	<b>-.449</b>	<b>.418</b>	<b>.588</b>	<b>1.000</b>	<b>.448</b>
	CTrstAI	<b>.058</b>	<b>.285</b>	<b>-.263</b>	<b>.704</b>	<b>.664</b>	<b>.448</b>	<b>1.000</b>
Sig. (1-tailed)	AlProdUse	.	<b>.003</b>	<b>.083</b>	<b>.086</b>	<b>.149</b>	<b>.044</b>	<b>.272</b>
	TPrecit	<b>.003</b>	.	<b>.000</b>	<b>.000</b>	<b>.001</b>	<b>.269</b>	<b>.001</b>
	Iss_Alprod	<b>.083</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.002</b>
	CAttAI	<b>.086</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	CDif	<b>.149</b>	<b>.001</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>

N	CdifCons	<b>.044</b>	<b>.269</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.</b>	<b>.000</b>
	CTrstAI	<b>.272</b>	<b>.001</b>	<b>.002</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.</b>
	AIProdUse	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TPrecit	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Iss_AIprod	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CAttAI	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CDif	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CdifCons	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	CTrstAI	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

52.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	<b>CTrstAI, Iss_AIprod, TPrecit, CdifCons, CAttAI, CDif<sup>b</sup></b>		<b>Enter</b>

a. Dependent Variable: AIProdUse

b. All requested variables entered.

53.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	<b>.319<sup>a</sup></b>	<b>.102</b>	<b>.051</b>	<b>1.164</b>	<b>.102</b>	<b>2.004</b>	<b>6</b>	<b>106</b>	<b>.072</b>

a. Predictors: (Constant), CTrstAI, Iss\_AIprod, TPrecit, CdifCons, CAttAI, CDif

b. Dependent Variable: AIProdUse

54.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>16.283</b>	<b>6</b>	<b>2.714</b>	<b>2.004</b>	<b>.072<sup>b</sup></b>
	Residual	<b>143.558</b>	<b>106</b>	<b>1.354</b>		
	Total	<b>159.841</b>	<b>112</b>			

a. Dependent Variable: AIProdUse

b. Predictors: (Constant), CTrstAI, Iss\_AIprod, TPrecit, CdifCons, CAttAI, CDif

55.

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>3.154</b>	<b>.724</b>		<b>4.355</b>	<b>&lt;.001</b>	<b>1.718</b>	<b>4.590</b>
	TPrecit	<b>.247</b>	<b>.090</b>	<b>.292</b>	<b>2.737</b>	<b>.007</b>	<b>.068</b>	<b>.426</b>
	Iss_AIprod	<b>.049</b>	<b>.088</b>	<b>.065</b>	<b>.557</b>	<b>.579</b>	<b>-.126</b>	<b>.224</b>
	CAttAI	<b>.081</b>	<b>.121</b>	<b>.099</b>	<b>.672</b>	<b>.503</b>	<b>-.158</b>	<b>.321</b>
	CDif	<b>-.068</b>	<b>.127</b>	<b>-.079</b>	<b>-.537</b>	<b>.593</b>	<b>-.321</b>	<b>.184</b>
	CdifCons	<b>.179</b>	<b>.093</b>	<b>.238</b>	<b>1.919</b>	<b>.058</b>	<b>-.006</b>	<b>.364</b>
	CTrstAI	<b>-.105</b>	<b>.114</b>	<b>-.132</b>	<b>-.926</b>	<b>.356</b>	<b>-.331</b>	<b>.120</b>

a. Dependent Variable: AIProdUse

56.

**Residuals Statistics<sup>a</sup>**

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>3.78</b>	<b>5.39</b>	<b>4.65</b>	<b>.381</b>	<b>113</b>
Std. Predicted Value	<b>-2.265</b>	<b>1.946</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.128</b>	<b>.632</b>	<b>.272</b>	<b>.100</b>	<b>113</b>
Adjusted Predicted Value	<b>3.69</b>	<b>5.45</b>	<b>4.65</b>	<b>.407</b>	<b>113</b>
Residual	<b>-3.735</b>	<b>1.798</b>	<b>.000</b>	<b>1.132</b>	<b>113</b>
Std. Residual	<b>-3.209</b>	<b>1.545</b>	<b>.000</b>	<b>.973</b>	<b>113</b>
Stud. Residual	<b>-3.310</b>	<b>1.681</b>	<b>.000</b>	<b>1.023</b>	<b>113</b>
Deleted Residual	<b>-4.450</b>	<b>2.143</b>	<b>-.001</b>	<b>1.256</b>	<b>113</b>
Stud. Deleted Residual	<b>-3.479</b>	<b>1.696</b>	<b>-.007</b>	<b>1.043</b>	<b>113</b>
Mahal. Distance	<b>.354</b>	<b>32.017</b>	<b>5.947</b>	<b>5.825</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.523</b>	<b>.017</b>	<b>.056</b>	<b>113</b>
Centered Leverage Value	<b>.003</b>	<b>.286</b>	<b>.053</b>	<b>.052</b>	<b>113</b>

a. Dependent Variable: AIProdUse

**57. Regression: Trust/BI**

**Descriptive Statistics**



	Mean	Std. Deviation	N
AlfutMK	<b>4.63</b>	<b>1.434</b>	<b>113</b>
TAccu	<b>4.42</b>	<b>1.266</b>	<b>113</b>
TRelDeci	<b>4.08</b>	<b>1.364</b>	<b>113</b>
TPrecit	<b>3.98</b>	<b>1.414</b>	<b>113</b>
TLearn	<b>4.75</b>	<b>1.177</b>	<b>113</b>
Tethic	<b>3.53</b>	<b>1.685</b>	<b>113</b>

58.

### Correlations

		AlfutMK	TAccu	TRelDeci	TPrecit	TLearn	Tethic
Pearson Correlation	AlfutMK	<b>1.000</b>	<b>.337</b>	<b>.298</b>	<b>.146</b>	<b>.522</b>	<b>.119</b>
	TAccu	<b>.337</b>	<b>1.000</b>	<b>.757</b>	<b>.408</b>	<b>.639</b>	<b>.473</b>
	TRelDeci	<b>.298</b>	<b>.757</b>	<b>1.000</b>	<b>.320</b>	<b>.552</b>	<b>.584</b>
	TPrecit	<b>.146</b>	<b>.408</b>	<b>.320</b>	<b>1.000</b>	<b>.443</b>	<b>.251</b>
	TLearn	<b>.522</b>	<b>.639</b>	<b>.552</b>	<b>.443</b>	<b>1.000</b>	<b>.342</b>
	Tethic	<b>.119</b>	<b>.473</b>	<b>.584</b>	<b>.251</b>	<b>.342</b>	<b>1.000</b>
Sig. (1-tailed)	AlfutMK	.	<b>&lt;.001</b>	<b>&lt;.001</b>	<b>.061</b>	<b>&lt;.001</b>	<b>.104</b>
	TAccu	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>
	TRelDeci	<b>.001</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	TPrecit	<b>.061</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.004</b>
	TLearn	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>
	Tethic	<b>.104</b>	<b>.000</b>	<b>.000</b>	<b>.004</b>	<b>.000</b>	.
N	AlfutMK	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TAccu	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TRelDeci	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TPrecit	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TLearn	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Tethic	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

59.

### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	<b>Tethic, TPrecit, TLearn,</b>	.	<b>Enter</b>

	<b>TRelDeci,</b>			
	<b>TAccu<sup>b</sup></b>			

a. Dependent Variable: AlfutMK

b. All requested variables entered.

60.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	<b>.536<sup>a</sup></b>	<b>.287</b>	<b>.254</b>	<b>1.239</b>	<b>.287</b>	<b>8.609</b>	<b>5</b>	<b>107</b>	<b>&lt;.001</b>

a. Predictors: (Constant), Tethic, TPrecit, TLearn, TRelDeci, TAccu

b. Dependent Variable: AlfutMK

61.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>66.095</b>	<b>5</b>	<b>13.219</b>	<b>8.609</b>	<b>&lt;.001<sup>b</sup></b>
	Residual	<b>164.295</b>	<b>107</b>	<b>1.535</b>		
	Total	<b>230.389</b>	<b>112</b>			

a. Dependent Variable: AlfutMK

b. Predictors: (Constant), Tethic, TPrecit, TLearn, TRelDeci, TAccu

62.

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>1.752</b>	<b>.520</b>		<b>3.372</b>	<b>.001</b>	<b>.722</b>	<b>2.783</b>
	TAccu	<b>.025</b>	<b>.157</b>	<b>.022</b>	<b>.161</b>	<b>.872</b>	<b>-.285</b>	<b>.336</b>
	TRelDeci	<b>.068</b>	<b>.144</b>	<b>.064</b>	<b>.470</b>	<b>.639</b>	<b>-.218</b>	<b>.353</b>
	TPrecit	<b>-.105</b>	<b>.094</b>	<b>-.103</b>	<b>-1.115</b>	<b>.268</b>	<b>-.292</b>	<b>.082</b>
	TLearn	<b>.669</b>	<b>.135</b>	<b>.548</b>	<b>4.943</b>	<b>&lt;.001</b>	<b>.400</b>	<b>.937</b>
	Tethic	<b>-.077</b>	<b>.086</b>	<b>-.090</b>	<b>-.893</b>	<b>.374</b>	<b>-.247</b>	<b>.094</b>

a. Dependent Variable: AlfutMK

63.

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N

Predicted Value	<b>2.33</b>	<b>6.14</b>	<b>4.63</b>	<b>.768</b>	<b>113</b>
Std. Predicted Value	<b>-2.989</b>	<b>1.967</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.155</b>	<b>.648</b>	<b>.270</b>	<b>.094</b>	<b>113</b>
Adjusted Predicted Value	<b>2.50</b>	<b>6.17</b>	<b>4.63</b>	<b>.765</b>	<b>113</b>
Residual	<b>-3.823</b>	<b>2.508</b>	<b>.000</b>	<b>1.211</b>	<b>113</b>
Std. Residual	<b>-3.085</b>	<b>2.024</b>	<b>.000</b>	<b>.977</b>	<b>113</b>
Stud. Residual	<b>-3.181</b>	<b>2.055</b>	<b>.000</b>	<b>1.003</b>	<b>113</b>
Deleted Residual	<b>-4.065</b>	<b>2.586</b>	<b>.001</b>	<b>1.277</b>	<b>113</b>
Stud. Deleted Residual	<b>-3.328</b>	<b>2.087</b>	<b>-.004</b>	<b>1.019</b>	<b>113</b>
Mahal. Distance	<b>.759</b>	<b>29.641</b>	<b>4.956</b>	<b>4.488</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.126</b>	<b>.009</b>	<b>.019</b>	<b>113</b>
Centered Leverage Value	<b>.007</b>	<b>.265</b>	<b>.044</b>	<b>.040</b>	<b>113</b>

a. Dependent Variable: AlfutMK

## 64. Regression: Trust/Actual use behaviour

### Descriptive Statistics

	Mean	Std. Deviation	N
AIProdUse	<b>4.65</b>	<b>1.195</b>	<b>113</b>
TAccu	<b>4.42</b>	<b>1.266</b>	<b>113</b>
TRelDeci	<b>4.08</b>	<b>1.364</b>	<b>113</b>
TPrecit	<b>3.98</b>	<b>1.414</b>	<b>113</b>
TLearn	<b>4.75</b>	<b>1.177</b>	<b>113</b>
Tethic	<b>3.53</b>	<b>1.685</b>	<b>113</b>

65.

### Correlations

		AIProdUse	TAccu	TRelDeci	TPrecit	TLearn	Tethic
Pearson Correlation	AIProdUse	<b>1.000</b>	<b>.334</b>	<b>.346</b>	<b>.255</b>	<b>.445</b>	<b>.249</b>
	TAccu	<b>.334</b>	<b>1.000</b>	<b>.757</b>	<b>.408</b>	<b>.639</b>	<b>.473</b>
	TRelDeci	<b>.346</b>	<b>.757</b>	<b>1.000</b>	<b>.320</b>	<b>.552</b>	<b>.584</b>
	TPrecit	<b>.255</b>	<b>.408</b>	<b>.320</b>	<b>1.000</b>	<b>.443</b>	<b>.251</b>
	TLearn	<b>.445</b>	<b>.639</b>	<b>.552</b>	<b>.443</b>	<b>1.000</b>	<b>.342</b>

Sig. (1-tailed)	Tethic	<b>.249</b>	<b>.473</b>	<b>.584</b>	<b>.251</b>	<b>.342</b>	<b>1.000</b>
	AIProdUse	.	<b>&lt;.001</b>	<b>&lt;.001</b>	<b>.003</b>	<b>&lt;.001</b>	<b>.004</b>
	TAccu	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>
	TRelDeci	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.000</b>	<b>.000</b>
	TPrecit	<b>.003</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>	<b>.004</b>
	TLearn	<b>.000</b>	<b>.000</b>	<b>.000</b>	<b>.000</b>	.	<b>.000</b>
N	Tethic	<b>.004</b>	<b>.000</b>	<b>.000</b>	<b>.004</b>	<b>.000</b>	.
	AIProdUse	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TAccu	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TRelDeci	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TPrecit	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	TLearn	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>
	Tethic	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>	<b>113</b>

66.

#### Variables Entered/Removed<sup>a</sup>

Model	Variables Entered	Variables Removed	Method
1	<b>Tethic, TPrecit, TLearn, TRelDeci, TAccu<sup>b</sup></b>	.	<b>Enter</b>

a. Dependent Variable: AIProdUse

b. All requested variables entered.

67.

#### Model Summary<sup>b</sup>

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	<b>.467<sup>a</sup></b>	<b>.218</b>	<b>.182</b>	<b>1.081</b>	<b>.218</b>	<b>5.973</b>	<b>5</b>	<b>107</b>	<b>&lt;.001</b>

a. Predictors: (Constant), Tethic, TPrecit, TLearn, TRelDeci, TAccu

b. Dependent Variable: AIProdUse

68.

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	<b>34.876</b>	<b>5</b>	<b>6.975</b>	<b>5.973</b>	<b>&lt;.001<sup>b</sup></b>

	Residual	<b>124.964</b>	<b>107</b>	<b>1.168</b>		
	Total	<b>159.841</b>	<b>112</b>			

a. Dependent Variable: AIProdUse

b. Predictors: (Constant), Tethic, TPrecit, TLearn, TRelDeci, TAccu

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	<b>2.303</b>	<b>.453</b>		<b>5.080</b>	<b>&lt;.001</b>	<b>1.404</b>	<b>3.202</b>
	TAccu	<b>-.039</b>	<b>.137</b>	<b>-.042</b>	<b>-.287</b>	<b>.775</b>	<b>-.310</b>	<b>.232</b>
	TRelDeci	<b>.113</b>	<b>.126</b>	<b>.129</b>	<b>.904</b>	<b>.368</b>	<b>-.135</b>	<b>.362</b>
	TPrecit	<b>.050</b>	<b>.082</b>	<b>.059</b>	<b>.611</b>	<b>.542</b>	<b>-.113</b>	<b>.213</b>
	TLearn	<b>.360</b>	<b>.118</b>	<b>.354</b>	<b>3.049</b>	<b>.003</b>	<b>.126</b>	<b>.594</b>
	Tethic	<b>.041</b>	<b>.075</b>	<b>.058</b>	<b>.544</b>	<b>.587</b>	<b>-.108</b>	<b>.189</b>

a. Dependent Variable: AIProdUse

#### Residuals Statistics<sup>a</sup>

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	<b>2.83</b>	<b>5.45</b>	<b>4.65</b>	<b>.558</b>	<b>113</b>
Std. Predicted Value	<b>-3.258</b>	<b>1.445</b>	<b>.000</b>	<b>1.000</b>	<b>113</b>
Standard Error of Predicted Value	<b>.135</b>	<b>.565</b>	<b>.235</b>	<b>.082</b>	<b>113</b>
Adjusted Predicted Value	<b>2.93</b>	<b>5.68</b>	<b>4.65</b>	<b>.554</b>	<b>113</b>
Residual	<b>-4.161</b>	<b>2.122</b>	<b>.000</b>	<b>1.056</b>	<b>113</b>
Std. Residual	<b>-3.850</b>	<b>1.964</b>	<b>.000</b>	<b>.977</b>	<b>113</b>
Stud. Residual	<b>-4.085</b>	<b>1.994</b>	<b>-.002</b>	<b>1.013</b>	<b>113</b>
Deleted Residual	<b>-4.683</b>	<b>2.188</b>	<b>-.004</b>	<b>1.135</b>	<b>113</b>
Stud. Deleted Residual	<b>-4.425</b>	<b>2.022</b>	<b>-.010</b>	<b>1.047</b>	<b>113</b>
Mahal. Distance	<b>.759</b>	<b>29.641</b>	<b>4.956</b>	<b>4.488</b>	<b>113</b>
Cook's Distance	<b>.000</b>	<b>.349</b>	<b>.013</b>	<b>.038</b>	<b>113</b>
Centered Leverage Value	<b>.007</b>	<b>.265</b>	<b>.044</b>	<b>.040</b>	<b>113</b>

a. Dependent Variable: AIProdUse

## 69. Cross-Tabulation Analysis



# Case Processing Summary

	Valid		Cases Missing		Total	
	N	Percent	N	Percent	N	Percent
Gender * AlfutMK	113	100.0%	0	0.0%	113	100.0%
Education * AlfutMK	113	100.0%	0	0.0%	113	100.0%
Income * AlfutMK	113	100.0%	0	0.0%	113	100.0%
Age * AlfutMK	113	100.0%	0	0.0%	113	100.0%

Gender \* AlfutMK (Chi-square showing no significant impact of Gender on AI perception)

## Crosstab

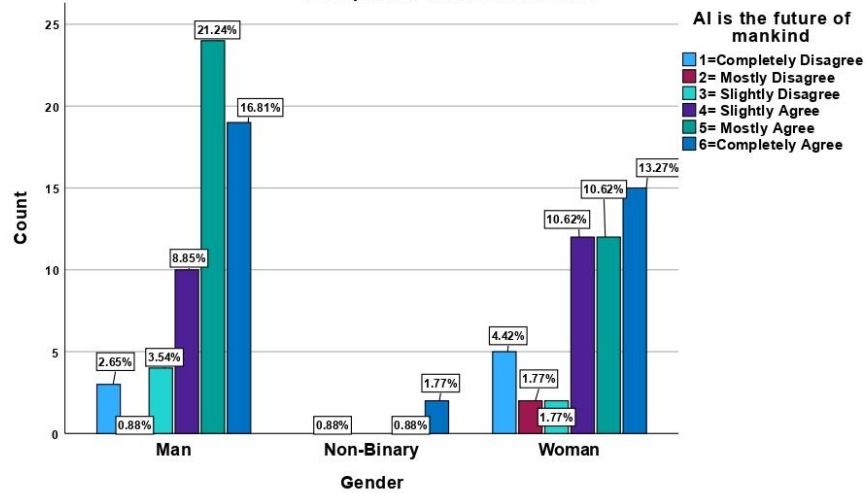
			AlfutMK						Total
			1	2	3	4	5	6	
Gender	Man	Count	3	1	4	10	24	19	61
		% within Gender	4.9%	1.6%	6.6%	16.4%	39.3%	31.1%	100.0%
	Non-Binary	Count	0	1	0	0	1	2	4
		% within Gender	0.0%	25.0%	0.0%	0.0%	25.0%	50.0%	100.0%
	Woman	Count	5	2	2	12	12	15	48
		% within Gender	10.4%	4.2%	4.2%	25.0%	25.0%	31.3%	100.0%
Total	Count	8	4	6	22	37	36	113	
	% within Gender	7.1%	3.5%	5.3%	19.5%	32.7%	31.9%	100.0%	

## Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11.852 <sup>a</sup>	10	.295
Likelihood Ratio	10.146	10	.428
N of Valid Cases	113		

a. 12 cells (66.7%) have expected count less than 5.  
The minimum expected count is .14.

## Perception of AI based on Gender



Crosstab

			AlfutMK					
			1	2	3	4	5	6
Education	Bachelors	Count	2	0	2	7	9	10
		% within Education	6.7%	0.0%	6.7%	23.3%	30.0%	33.3%
	Doctorate	Count	0	0	2	1	3	8
		% within Education	0.0%	0.0%	14.3%	7.1%	21.4%	57.1%
	High school	Count	3	3	1	4	2	4
		% within Education	17.6%	17.6%	5.9%	23.5%	11.8%	23.5%
	Masters	Count	3	1	1	10	23	14
		% within Education	5.8%	1.9%	1.9%	19.2%	44.2%	26.9%
	Total		Count	8	4	6	22	37
% within Education			7.1%	3.5%	5.3%	19.5%	32.7%	31.9%

Crosstab

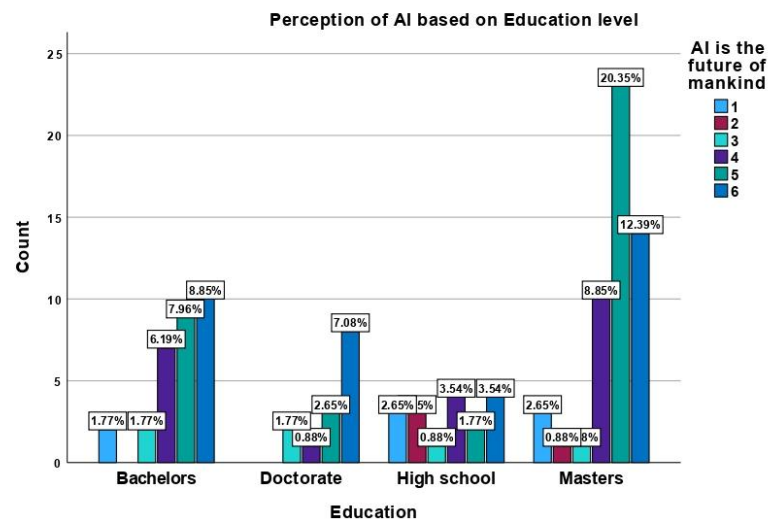
			Total
Education	Bachelors	Count	30
		% within Education	100.0%
	Doctorate	Count	14
		% within Education	100.0%
	High school	Count	17
		% within Education	100.0%
	Masters	Count	52
		% within Education	100.0%
Total	Count	113	
	% within Education	100.0%	

Chi-Square Tests Education level on AI perception

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	28.730 <sup>a</sup>	15	.017
Likelihood Ratio	26.007	15	.038

a. 16 cells (66.7%) have expected count less than 5.  
The minimum expected count is .50.





#### Income \* AlfutMK

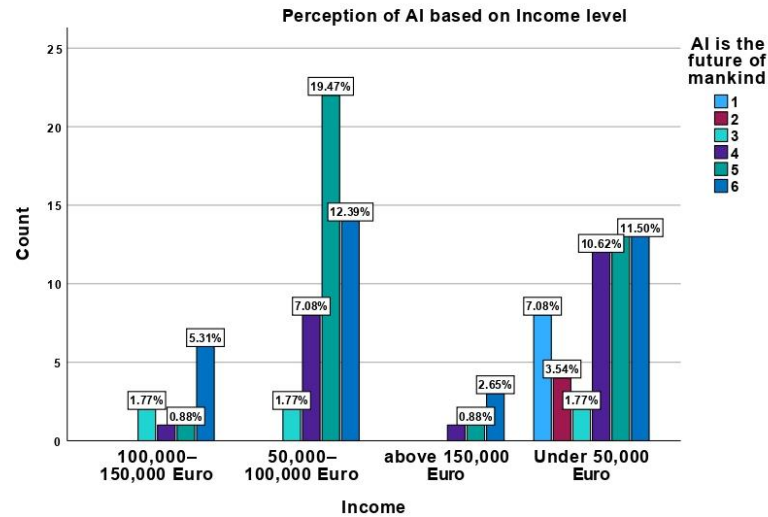
Crosstab								
			AlfutMK					
			1	2	3	4	5	6
Income	100,000–150,000 Euro	Count	0	0	2	1	1	6
		% within Income	0.0%	0.0%	20.0%	10.0%	10.0%	60.0%
	50,000–100,000 Euro	Count	0	0	2	8	22	14
		% within Income	0.0%	0.0%	4.3%	17.4%	47.8%	30.4%
	above 150,000 Euro	Count	0	0	0	1	1	3
		% within Income	0.0%	0.0%	0.0%	20.0%	20.0%	60.0%
	Under 50,000 Euro	Count	8	4	2	12	13	13
		% within Income	15.4%	7.7%	3.8%	23.1%	25.0%	25.0%
Total	Count	8	4	6	22	37	36	
	% within Income	7.1%	3.5%	5.3%	19.5%	32.7%	31.9%	

			Crosstab
			Total
Income	100,000–150,000 Euro	Count	10
		% within Income	100.0%
	50,000–100,000 Euro	Count	46
		% within Income	100.0%
	above 150,000 Euro	Count	5
		% within Income	100.0%
	Under 50,000 Euro	Count	52
		% within Income	100.0%
Total	Count	113	
	% within Income	100.0%	

# Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	30.109 <sup>a</sup>	15	.012
Likelihood Ratio	32.947	15	.005
N of Valid Cases	113		

a. 18 cells (75.0%) have expected count less than 5.  
The minimum expected count is .18.



## Age \* AlfutMK

### Crosstab

			AlfutMK						
			1	2	3	4	5	6	Total
Age	18-24	Count	1	2	0	4	5	7	19
		% within Age	5.3%	10.5%	0.0%	21.1%	26.3%	36.8%	100.0%
	25-34	Count	3	2	2	8	16	16	47
		% within Age	6.4%	4.3%	4.3%	17.0%	34.0%	34.0%	100.0%
	35-44	Count	1	0	1	5	8	8	23
		% within Age	4.3%	0.0%	4.3%	21.7%	34.8%	34.8%	100.0%
	45-54	Count	0	0	2	1	3	4	10
		% within Age	0.0%	0.0%	20.0%	10.0%	30.0%	40.0%	100.0%
	55-64	Count	0	0	0	4	2	1	7
		% within Age	0.0%	0.0%	0.0%	57.1%	28.6%	14.3%	100.0%
	65 and above	Count	3	0	1	0	3	0	7
		% within Age	42.9%	0.0%	14.3%	0.0%	42.9%	0.0%	100.0%
Total	Count	8	4	6	22	37	36	113	
	% within Age	7.1%	3.5%	5.3%	19.5%	32.7%	31.9%	100.0%	

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	36.346 <sup>a</sup>	25	.067
Likelihood Ratio	32.919	25	.133
N of Valid Cases	113		

a. 29 cells (80.6%) have expected count less than 5.  
The minimum expected count is .25.

