FACING ARTIFICIAL INTELLIGENCE

FROM SIMPLE PRODUCT RECOMMENDATIONS

TO COMPLETE LIFESTYLE DESIGN

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DECLARATION OF ORIGINALITY

I, Ayşe Mine Yurdagel, certify that

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ABSTRACT

Facing Artificial Intelligence

From Simple Product Recommendations to Complete Lifestyle Design

The late expeditious development of Artificial Intelligence (AI) contains both appreciations and concerns in regard of its potential. Nevertheless, despite all its technological potential, its future also depends on how much people will acknowledge it. This study takes a marketing perspective and presents a contribution by offering answers, explanations and predictions regarding AI acceptance in consumption domain.

The study investigates insights of consumers' AI acceptance by taking a well-known and familiar AI application as an example, recommendations at online shopping. With the help of a unifying methodology including an experiment and a survey, AI acceptance is challenged at a comparison to a Human advisor together with the presentations of the reasons behind, and a future projection. Results indicate that in such a challenge AI is behind a Human advisor. AI is attributed with lower trust, both at cognitive and emotional dimensions. In addition, in adopting the recommendation, whereas for Human advisor emotional trust is as crucial as cognitive trust, for AI condition emotional trust becomes insignificant. In terms of functionality, the recommendation received from AI is perceived as being less useful, and the process of receiving the recommendation is evaluated as less transparent. Lastly, results regarding an enhanced AI competence, mimicking a projection of the future, showed that the differentiation between AI and Human advisors observed at previous steps remain consistent.

ÖZET

Yapay Zeka ile Yüzleşme

Basit Ürün Önerilerinden Bütün Yaşam Tarzı Tasarımına

Son dönemlerdeki hızlı gelişimi ile Yapay Zekâ, potansiyeli konusunda bir yandan takdir toplarken diğer yandan endişelere sebep olmaktadır. Fakat Yapay Zekâ'nın geleceği teknolojik potansiyelinin yanı sıra insanların onu ne kadar kabul edeceklerine de bağlıdır. Çalışma çerçevesinde konuya pazarlama açısından bakılmakta ve tüketim alanında Yapay Zekâ kabulüne ilişkin cevaplar, açıklamalar ve öngörüler sunulmaktadır.

Çalışmada, iyi bilinen ve alışılmış bir Yapay Zekâ uygulaması olan çevrimiçi alışveriş önerileri temel alınarak Yapay Zekâ kabulüne ilişkin tüketici içgörüleri araştırılmıştır. Hem deney kurgusu hem de anket çalışması içeren kapsamlı bir meteodoloji kullanılarak Yapay Zekâ bir insan danışman ile karşılaştırılmış, sürecin arka planındaki etkenler sorgulanmış ve geleceğe dönük bir projeksiyon sunulmuştur. Sonuçlar, Yapay Zekâ'nın aldığı kabulün bir insan danışmanın gerisinde olduğunu göstermiştir. Yapay Zekâ, bir insan danışmana göre hem bilişsel hem de duygusal boyutlarda daha düşük güven ile ilişkilendirilmektedir. Aynı zamanda, bir insan danışmana geliştirilen duygusal güven bilişsel güven kadar önem taşırken, Yapay Zekâ açısından bakıldığında duygusal güven etkisiz hale gelmektedir. İşlevsellik açısından ise, Yapay Zekâ 'dan alınan öneri daha az faydalı olarak algılanmış ve öneri alma süreci daha az şeffaf olarak değerlendirilmiştir. Son olarak da, geleceği taklit eden farklı yetkinlikteki Yapay Zekâ projeksiyonlarında, Yapay Zekâ ve insan danışman arasında önceki adımlarda gözlenen farklılıkların tutarlı kaldığı belirlenmiştir.

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This dissertation is dedicated to

my father Hasan and my mother Saliha,

my sister Hülya and my niece Dila,

and my daughter Elif

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX TABLES

ABBREVIATIONS

AI Artificial Intelligence

ANOVA Analysis of Variance

AVE Average Variance Extracted

CASA Computers Are Social Actors

CFA Confirmatory Factor Analysis

CFI Comparative Fit Index

CT Cognitive Trust

CTAb Cognitive Trust Ability

CTBen Cognitive Trust Benevolence

CTIn Cognitive Trust Integrity

Df Degrees of Freedom

EFA Exploratory Factor Analysis

ET Emotional Trust

ETBIS Elektronik Ticaret Bilgi Sistemi

INT Intention to Adopt

KMO Kaiser-Meyer-Olkin

MANOVA Multivariate Analysis of Variance

MSA Measure of Sampling Adequacy

NFI Normed Fit Index

PU Perceived Usefulness

PEoU Perceived Ease of Use

RFI Relative Fit Index

RMSEA Root Mean Square Error of Approximation

SEM Structural Equation Modeling

SRMR Standardized Root Mean Square Residual

SIG Significance

SP Social Presence

TAM Technology Acceptance Model

TRA Theory of Reasoned Action

TÜSİAD Türkiye Sanayici ve İş İnsanları Derneği

UTAUT, Unified Theory of Acceptance and Use of Technology

CHAPTER 1

INTRODUCTION

Artificial Intelligence (AI) is considered to be similar to electricity in terms of technology. It is evaluated to have a comparable importance and value due to its potential impact size, its competency to diffuse into several different areas, and its capability to cause a domino effect for other innovations (Brynjolfsson & Mcafee, 2017). However, it is not sufficient to comment on AI from a technological perspective only. AI is mixing into lives of people, in other words it involves the digital world of future generations (Cath, Wachter, Mittelstadt, Taddeo, & Floridi, 2018).

The inseparable relation of AI and people is observed in the past, specifically at the late developments of this technology. AI is not brand new, but gained a high momentum within the last years (Haenlein & Kaplan, 2019). At this momentum, in addition to the realized technological progress steps, the ever-enhancing digital life of people is very influential as well. This impact led AI to enjoy data abundance (Hey, 2010). In other words, AI prospers with data (Cath et al., 2018) and every member of the digital world is providing AI the necessary sources, continuously every second.

Second, AI and people seem to be intertwined in future as well. In spite of all the progress made so far, there is still a big potential at AI domain, and for the society's benefit, it is a question whether this potential shall be realized or not. The full expectancy from AI is to catch and may be surpass human intelligence and it is not reached yet (Brynjolfsson & Mcafee, 2017). In fact, AI is accepted to be only at the first phase. AI of today is considered as narrow and weak, since it is powerful at one subject only and cannot transfer this expertise to different areas (Hengstler, Enkel, & Duelli, 2016). It can compete and beat a human easily within a given domain but is not comparable to human intelligence in a more horizontal understanding. Next steps of the typology cover general AI and super AI, where one considers having a human intelligence, a learning capacity and an understanding at all areas of analytical, emotional and social intelligence, and the other asks for a consciousness on top (Kaplan & Haenlein, 2019). Scientists of the domain agree that a general AI will be achieved in year 2075; however they are not very optimistic about the benefits of going further to the next step, i.e. to a super AI (Müller & Bostrom, 2016). Whereas actual concerns of AI such as black box mentality (Haenlein & Kaplan, 2019), control of consumer free will (André et al., 2018), and manipulative power (Mazurek & Małagocka, 2019) are not solved yet, the potential future impact of AI on society is raising additional questions (Acemoglu & Restrepo, 2018; Dholakia & Firat, 2019; Huang & Rust, 2018).

While scientists work to catch the human intelligence and discuss the macro social impact within the next 50 years, it is essential to understand how ordinary people will react to these changes as well. Their acceptance of AI, from sharing power at a job environment to having a social interaction with it, shall shape the future of this technology. A marketing perspective can provide an important contribution at this point, as marketing lies in the intersection between production and consumption, and shall get the major role within the reallocation of the resources at the changing environment (Dholakia & Firat, 2019; Grewal, Hulland, Kopalle, & Karahanna 2020; Schmitt, 2019). In other words, understanding production and consumption at the same time, marketing can orient AI developments and utilization.

The technological forces within the sphere of men and machine interaction can force marketing itself to experience a metamorphosis as well (Kumar, 2018). While the subject, whether marketing will be the master of AI or will surrender their rights and duties to it, is in speculation (Davenport, Guha, Grewal, & Bressgott, 2020; Kozinets & Gretzel, 2021; Overgoor, Chica, Rand, & Weishampel, 2019), it is for sure that the marketers able to use AI will eliminate those who are not (Brynjolfsson & Mcafee, 2017).

Marketing literature lacks studies in AI (Davenport et al., 2020). Aiming to provide an input in this realm, this study uses a marketing perspective and works on insights in AI technology acceptance. The targets of the study are answering the question of how consumers perceive AI, explaining the reasons of this feedback, and predicting in what way this perception can evolve with future developments of the technology.

1.1 Motivation of the study

The concept of Artificial Intelligence is very powerful in wording; it resembles myths, and has such an aura as if it covers anything and everything (Donath, 2021). For an average person, AI could sound too futuristic, and belonging to science labs, space exploration, or science fiction movies. However, every consumer faces AI every day under different names. It could be by internet searches, at navigation applications, or during conversations with voice assistants like Apple's Siri, Google Assistant, or Amazon's Alexa.

This study particularly focuses on a major meeting point with AI in daily consumption, namely online shopping recommendations. Thus, recommendations are taken as a natural extension of AI technology in marketing and recommendation adoption is reflected to a general AI acceptance. Recommendations are a typical AI application; they work on enormous data, adapt to the changing information, and provide a valuable output. On the other hand, the value of recommendations in marketing is essential, i.e., understanding the need of a customer and addressing this need with the optimum offer.

Recommendations offer great help to the customer because in online shopping world "there are both more needles and more hay" (Adomavicius, Bockstedt, Curley, Zhang, & Ransbotham, 2019). Accordingly, the value of recommendations and the appreciation of customers are obvious at recommendation effectiveness literature and actual sales results of online shopping platforms (e.g., Accenture Personalization Pulse Check, 2018; Banker & Khetani, 2019; Häubl & Trifts, 2000; Leavitt, 2006; Love, 2014). The literature questioning recommendations embraced the subject more from a technical point of view rather than a consumer feedback one (Adomavicius, Bockstedt, Curley, & Zhang, 2018; Baier & Stüber, 2010; Dabholkar & Sheng, 2012; Gai & Klesse, 2019; Martínez-López, Esteban-Millat, Argila, & Rejón-Guardia, 2015; Wang & Benbasat, 2008). Some studies compared the impact of different technologies utilized for making recommendations (e.g. Adomavicius et al., 2019; Dabrowski & Acton, 2013) or worked on the changes experienced for different product types or for different consumer characteristics (e.g. Aljukhadar, Trifts, & Senecal, 2017; Helmers, Krishnan, & Patnam, 2019; Lee & Hosanagar, 2021; Pathak, Garfinkel, Gopal, Venkatesan, & Yin, 2010). Yet some others questioned the effect on purchase funnel (e.g. Kumar, Wan, & Li, 2020; Pöyry, Hietaniemi, Parvinen, Hamari, & Kaptein, 2017; Zhang & Bockstedt, 2020), and figured out the macro effects on product variety and consumer well being (Fong, Zhang, Luo, & Wang, 2019; Kim, Albuquerque, & Bronnenberg, 2010; Lee & Hosanagar, 2019).

However, the ultimate target of AI technology is to reach human intelligence and it is speculated to getting closer to this target each day (Müller & Bostrom, 2016). Hence, for the speculated future, a direct comparison to a Human advisor can provide additional insights. In other words, the effectiveness of recommendations cannot be totally understood within the boundaries of the digital world, where there is no other choice than an AI recommendation. If at the same medium the consumers had the possibility to receive a recommendation from a human as well, would AI recommendations keep their worth? The answer to this question could help to predict and understand the reactions at other domains where AI will face humans or come into competition with them such as services sector.

Where recommendation effectiveness literature does not focus on that question, advice source comparison literature does. In this literature stream, the branch of algorithm adoption considers AI as the comparable advice source and is a newer branch compared to recommendation effectiveness. It mostly compares the reaction to AI and Human advisors and focuses on specific cases like driverless cars, medical sector AI utilization or robots (e.g. Castelo, Bos, & Lehmann, 2019; Dietvorst, Simmons, & Massey; 2015; Gill, 2020; Logg, Minson, & Moore, 2019; Longoni, Bonezzi, & Morewedge, 2019; Luria et al., 2019; Yeomans, Shah, Mullainathan, & Kleinberg, 2019).

This study combines these two literature streams in questioning the online recommendation adoption at a challenge against a Human advisor. Taking into consideration that the answers achieved so far by the algorithm adoption literature are confusing (Jussupow, Benbasat, & Heinzl, 2020), and that the recommendation effectiveness literature is limited to the AI perspective, such a combination could offer extra insights for both. In particular, for recommendation effectiveness literature, the models applied and the results achieved so far can be audited whether or not holding at a direct comparison to a Human advisor. On the other hand, for the algorithm adoption literature, the reasons behind a preference between AI and Human advisors can be detailed.

To understand the reasons behind such a preference, the study utilizes a unifying perspective and questions both cognitive and emotional impacts within the process. AI is a new technology, but functionality shall not be enough for its adoption. In online shopping, the scope of this study, evaluating only the cognitive dimension is neither sufficient nor effective (Bleier, Harmeling, & Palmatier, 2019). Emotional aspects shall intervene into the process since consumers act both with rational and emotional motivations (Holbrook & Hirschman, 1982) and analyzing both motivations simultaneously will help to understand each one's value in specific.

Lastly, the study aims to go one-step further and shed a light on the future by comparing AI and Human advisors within a series of gradually empowering recommendations. AI is expected to develop further and it is relevant to foresee how people will face this progress. Almost one hundred year ago, in 1933, the World Fair in Chicago used the motto "Science Finds- Industry Applies- Man Conforms" (Mick & Fournier, 1998). This loop could have been effective until now. However, the line between human and machine is not fixed and changes with time (Waytz, Heafner, & Epley, 2014). AI science is advancing as discussed above. In terms of industry reaction, especially with the expanded digital world after the Covid19 pandemic, more and more investments are observed (McKinsey Global AI Survey, 2020). Nevertheless, taking the rising concerns about and the controversial nature of AI into consideration, can we still assume that man would conform as before? In other words, will people surrender to technology as stated by Walker (2016) or will there be a breaking point?

1.2 Methodology

The study relies on recommendation effectiveness and AI adoption literatures. Recommendation effectiveness studies collect data with questionnaires, benefit theoretical models like Technology Acceptance Model to clarify the relationships, and operate with regression analysis or Structural Equation Modeling (SEM) studies to evaluate the results. AI adoption literature works mainly with experiments and uses comparative analysis to comment on data.

The methodological aim of the study is to benefit the strongest points of both literature streams. Therefore, data is collected simultaneously by an experiment and a questionnaire, and the results are worked through separate analysis methods. Having the same sample to attend the experimental process and answer the questionnaire at the same time, contribute to understand the dynamics behind the scene. Accordingly, the study first questions the preference between AI and Human advisors and then interrogates detailed mechanisms behind this preference. Group comparison tools examine the first part, whereas for the rest of the study a SEM analysis is realized.

The study, at both the experiment and the questionnaire stages, is based on a vignette describing an online shopping experience of sneakers. Footwear is one of the most sold items in online shopping (Statista, 2018) and sneakers appeal to both genders, to all income levels, and to any age group. Depending on the manipulation type, participants receive recommendations from two different sources, AI or Design Team, about four different types of products, simply another alternative sneaker model, a sneaker model produced with environmentally conscious material but slightly higher in price, a backpack to accompany sneakers, and a sneaker model designed specifically by the recommendation source.

This vignette utilizes a contemporary recommendation understanding, namely it provides proposals by itself without asking for a customer input beforehand. Recommendations differ whether they ask questions to the user to state their needs and wants or automatically work in background (Dabholkar & Sheng, 2012). The literature, especially at the beginning period of recommendation studies, mainly used the first type (Benbasat & Wang, 2005; Komiak & Benbasat, 2006; Wang & Benbasat, 2008). However, technology is always reshaping (Bauman & Bachmann, 2017). Although the feature-based recommendations for specifically stated needs are still used in online shopping mostly as a filtering, the contemporary AI based recommendations are dynamic and do not collect needs or wants from the user directly. They work automatically in the background to provide customer specific proposals (Kumar et al., 2019). Updated studies are needed (Benbasat & Wang, 2005) and this study is in line with this call in terms of methodology.

1.3 Findings

The study aimed to test consumers' AI acceptance in the boundaries of a well-known and familiar example, recommendations at online shopping. This acceptance is compared to the one, which would be provided to a Human advisor. Additionally, the impacting factors within the process are questioned, and by increasing the scope of the recommendation, a future projection is realized.

Supporting the algorithm aversion literature, results demonstrate that a Human advisor is preferred in fashion specific recommendations (Castelo et al., 2019; Dietvorst et al., 2015; Dietvorst, 2016; Luo, Tong, Fang, & Qu, 2019; Önkal, Goodwin, Thomson, Gönül, & Pollock, 2009; Promberger & Baron, 2006; Yeomans et al., 2019). As clothing has the highest percentage of online shoppers (Eurostat, 2021) and as both literature (e.g. Banker & Khetani, 2019; Häubl & Trifts, 2000; Leavitt, 2006) and practical reports (Accenture Personalization Pulse Check, 2018; Love, 2014) state that recommendations are effective in shopper decisions, this result may seem astonishing at first sight. However, it should be noted that the study describes a different condition than the existing familiar online shopping environment; a challenger to online recommendations is put forward, namely a Human advisor. Thereby, the results still confirm that AI receives a general acceptance in terms of online shopping recommendations, however it struggles when there is a human alternative.

The reasons behind the preference of a human alternative in such a challenge are that AI is rated lower at all aspects of cognitive trust, i.e. ability, integrity, and benevolence, as well as emotional trust. In addition, when a recommendation is received from AI, it is perceived as less useful and the process is evaluated as being more difficult to understand. Then, when the race starts, i.e. when cognitive trust, emotional trust, perceived ease of use, and perceived usefulness structure together to build an intention to adopt the received recommendation, AI loses one of these assets completely. When the recommendation is received from AI, emotional trust to the advisor becomes insignificant and has not any direct or indirect impact.

Results stress the importance of social and emotional feedback of people to AI. Accordingly, ensuring positive social and emotional conditions shall be as important as technological development in the domain. In addition to providing a psychological perspective to AI acceptance for the actual situation, the viewpoint is projected into future as well. By letting the delivered recommendations getting more advanced at four different steps, the study mimics an empowering AI, and reanalyzes the challenge between AI and Human advisors at these different steps. The results can be evaluated both at demand and supply sides, impacting consumption environment and job markets respectively.

In terms of consumption realm, when compared against a Human advisor, the potential reactions to the future AI seem not different from the actual feedback. The preference of a Human advisor remained stable all along the manipulated advancing recommendation types, reflecting an empowering AI. Neither at the basic level, which is a common method met every day at online shopping nor at the design, which is a creative domain and is rare at online shopping platforms as of today, a discrepancy is observed. The reasons can be speculated as people having a general bias against AI (Luo et al., 2019), putting the emphasis on the offered product rather than the source (Jago, 2019; Köbis & Mossink, 2021), or acknowledging developers of AI along the technology at every level (Epstein, Levine, Rand, & Rahwan, 2020). In addition to these possible explanations, the disfavor of AI in relation to the lacking emotional connection shows that the role of emotions in consumption, stressed by Holbrook and Hirschman (1982), will remain essential in the future digital world, if not enhanced (Huang et al., 2019).

In terms of supply side, clues are collected concerning the future job market. Big technology breakthroughs always frightened people about losing their jobs and AI is not an exception. With developing further and further, AI gains power to diminish the needed headcount to finalize a task or even to totally replace human workers. This replacement can be at production sites as well as service environments facing the customer directly. The study posits that when facing a customer, although the functional capability of AI can be enormous, it can still be behind humans in terms of social and emotional evaluations. That is when having a chance to be served either by AI or by a human, the preference will not be favoring AI. In such terms this preference may even cost higher, that is people may be ready to pay more to receive the same service from a human provider and not AI (Brock & Von Wangenheim, 2019). This preference can be mostly observed at subjective and socially interactive domains, where emotional aspects are essential. Developments in AI are expected to create new jobs for humans or in other words let humans to shift to new areas whenever their initial spot is lost to AI (Acemoglu & Restrepo, 2018). These new jobs are expected to be realized in intuitive and empathetic domains (Huang & Rust, 2018). The results of the study confirm that humans will gain over AI in terms of social and emotional conditions, in line with the proposition that in future AI shall take place at cognitive jobs and leave emotion oriented ones to humans (Huang, Rust, & Maksimovic, 2019).

1.4 Outline

The study will start with the Literature Review section defining AI, stressing its importance, and summarizing its utilization first within a general business frame, then specifically at marketing. Then as a tool of AI in marketing, recommendations will be introduced and two literature streams questioning recommendation effectiveness and advice source comparison will be presented. After the Theoretical Framework section, which is structured by technological and social perspectives, Constructs are discussed in detail, and Hypotheses are developed. In the Research Methodology section, the experimental study is presented with details together with data collection methods and utilized measures.

The Results section provides the Profile of the Sample, the Data Structure, the Scale Validations, and the Hypotheses Testing. The Hypotheses Testing section has four parts, questioning the choice between AI and Human advisors in intention to adopt the recommendation, differentiating cognitive and emotional trust given into each recommendation source, detailing perceived ease of use and perceived usefulness of the recommendation received from the two sources, and analyzing the path relationships within the model. Results are commented in the Discussion section and implications are shared in the Conclusions, Implementations, and Limitations section.

The flow of the experiment in English (see Appendix A) and in Turkish (see Appendix B); scales (see Appendix C); profile of the sample (see Appendix D); details of exploratory factor analysis (see Appendix E) and confirmatory factor analysis (see Appendix F); statistical details of hypotheses analyses for Study 1 (see Appendix G); data normality plots and statistical details of hypotheses analyses for Study 2 (see Appendix H and Appendix I), data normality plots and statistical details of hypotheses analyses for Study 3 (see Appendix J and Appendix K), and comparative model figure and comparative model statistical analysis for Study 4 (see Appendix L and Appendix M) are shared within appendices.

CHAPTER 2

LITERATURE REVIEW

2.1 Artificial Intelligence in general

2.1.1 Definition, technical development, and growth factors

AI is a difficult concept to define. There are two main issues building up this difficulty. First, it is hard to define intelligence for humans, and consecutively it is hard to conceptualize which part and how much of human intelligence shall be reflected into an artificial substance (Kaplan & Haenlein, 2019). For example, although now considered as an indispensable part of intelligence, emotional intelligence concept gained popularity at mid 90s, and only after then the definition of human intelligence covered understanding and controlling emotions in addition to memory, problem solving and analyzing (Dhani & Sharma, 2016).

The second difficulty in defining AI relies on a concept called AI effect (Haenlein & Kaplan, 2019). The pace of technological developments causes any AI novelty, welcomed as a high technology artifact at first, to be considered as an ordinary tool in a very short period. After reaching masses and becoming a tool of daily life, an AI novelty loses its magic and is perceived as less intelligent.

Having these concerns in mind, AI can be defined in line with the actual understanding and scope of intelligence and the technological position achieved as of today. Accordingly, AI refers to all systems capable of perceiving data in any one of various forms such as numbers, text, sound or visuals, then learn according to the data collected, convert the data into information, derive a meaning, and use these results to realize the target (Brynjolfsson & Mcafee, 2017; Davenport et al., 2020; Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019).

AI started its journey in 1947 when Alan Turing mentioned intelligent machines for the first time (Haenlein & Kaplan, 2019). However, the official birth date is acknowledged as 1956 since at that time a seminar about the subject is realized at Dartmouth College. The documentation prepared for this seminar included the term AI for the first time and John McCarthy, one of the professors organizing the seminar, is accepted as the father of the concept (Brynjolfsson & Mcafee, 2017).

Having a history of about 70 years, AI traveled through different eras where attention to the subject has alternatively shined and faded (Cath et al., 2018). The high levels of public attention, research funding and academic studies at the beginning were lost with time since the expectations from AI was set too high and could not be achieved (Brynjolfsson & Mcafee, 2017; Haenlein& Kaplan, 2019). However, a new brightening period started when games were used for AI developments. The aim of developing AI systems at games was to achieve progress, measure it, and transfer this understanding to more general-purpose areas (Gibney, 2017). The progress of AI is observed first at chess, when an AI system capable to process 200 million moves in a second and foresee the possibilities of each move 20 step further, beat the world champion in 1997 (Campbell, Hoane, & Hsu, 2002). This victory created excitement among the scientists of the AI domain and had been appreciated within chess circles. Nevertheless, the real stage introducing AI to the ordinary people was the television. In 2011, within Jeopardy, a TV game show in the form of a quiz, AI won against the other two contestants, who had been among the most successful ones of the show (Gabbatt, 2011; IBM, 2020). Then in 2017, AI showed its potential at the Asian game of Go by demonstrating very novel moves and surpassing the accumulated knowledge of people over hundreds of years (DeepMind, 2017).

The victories at games were following a technical evolution behind the scenes. At the initial stages, when playing chess, AI was only an expert system working according to the algorithm specified by a human (Davenport et al., 2020; Haenlein & Kaplan, 2019). An algorithm defines strictly which data is necessary, how and when to use this data, when to pass to the next step, and when and how to know that the aim is reached (Lexico, n.d). Accordingly, an expert system AI is bounded with these specifications. As not having learning capability, it did not have the essence of the actual definition of AI as of today (Kaplan & Haenlein, 2019). However, at the next steps, AI gets independent of humans through learning by itself. First step was machine learning.

In 1980s, machine learning technique emerged where the system was taught of human thinking methods (Brynjolfsson & Mcafee, 2017; Jeffcock, 2018; Stanford, n.d.). At machine learning, AI uses the data on hand and works by itself to reach meaningful results by looking for patterns within the data or finding outlier items (Murphy, 2012). The human intervention could be either in solving first a smaller size puzzle to teach the system the working method, or in showing key variables for the solution, or in defining the expected targets of the main outcomes (Brynjolfsson & Mcafee, 2017; Jeffcock, 2018; Kaplan & Haenlein, 2019; Overgooret al., 2019).

Then since 2010s, machine learning has evolved to deep learning, which sticks to the mentality of working independent from human intervention, but utilizes a new technology (Jeffcock, 2018). In deep learning, the neural network of the human brain is simulated, that is, nodes are grouped in layers, then they form a network, and data is passed from one node to the other, from one layer to the next (TED, 2015). This development both supported and benefited from the changes in the digital world. Namely, digital information has been evolving from text and numbers to visual data, such as at the social media platforms Instagram and Youtube, and thanks to deep learning, AI has been capable to work with these different types of data (Liu, Dzyabura, & Mizik, 2020). Nevertheless, visual data availability reinforced the progress of deep learning as well. Accordingly, the miracles of AI started to be real one after the other like face recognition, speech communication and driverless cars (Brynjolfsson & Mcafee, 2017; Haenlein & Kaplan, 2019; Jeffcock, 2018; Leavitt, 2006; Schafer, Konstan, & Riedl, 2001).

In addition to developments in technological methods like machine learning and deep learning, there are two other resources affecting the lately observed growth at AI impact size and diffusing areas, namely hardware developments and data availability (Cath et al., 2018; Overgoor et al., 2019). First, thanks to the progress in hardware solutions, AI systems could analyze big amounts of data, calculate results, and offer solutions, even in areas with a need of high capacity utilization (Hey, 2010).

On the other hand, the availability of abundant data was a real driving force for AI. AI needs data to work with and today data is flowing and accumulating with a very high speed from all over the world (Hey, 2010). Data is considered as the oil of the digital economy by being a valuable raw material or ingredient for various activities, but being better than oil, data could be replenished and reused (Mazurek & Małagocka, 2019). In digital world, it is easy, fast, and efficient to reach data, as first, people are loading their information to the system by their own will, and second, mechanical products are becoming a source of data through Internet of Things (Wedel & Kannan, 2016).

Being technically rid of the two impediments, dependence to humans and limitation in data types, and getting the support of hardware developments and data abundance, AI passed an important milestone (Adomavicius & Tuzhilin, 2005). Thanks to the success achieved and to the role gained in the daily lives of people, it gets into the radar of the business world (Haenlein& Kaplan, 2019).

2.1.2 Utilization in business

AI shows a steady growth in terms of diffusing to business operations. In 2021, 56% of companies reported AI utilization in minimum one business function, showing an increase of 12% compared to 2020 (McKinsey Global AI Survey, 2021). AI applications are not off the shelf solutions, hence utilization areas can be widely different at each company from product development to supply chain management, from actual manufacturing to human resources, and from marketing to strategy setting (McKinsey Global AI Survey, 2020).

The decision of where and how to utilize AI technology within the company shall depend on the intersection of the areas, where most value can be created in the specific environment and where AI could bring most add on (Chui, Henke, & Miremadi, 2018). Some companies can prefer AI improvements in process management, forecast accuracy, and customer analytics to get revenue increases, where others can invest in AI to enhance automation and employment process for cost decreases (McKinsey Global AI Survey, 2020).

Being more specific and looking at different business processes, a company can use AI for hiring, motivation, training, and appraisal in human resources management and enjoy savings in time and effort (Tambe, Cappelli, &Yakubovich, 2019; Wilson &

Daugherty, 2018). For example, algorithms developed according to the actual employee records, can be used to find the most promising candidate for the company (Kuncel, Klieger, & Ones, 2014); or concerns, goals, and needs of actual employees can be analyzed by AI to prevent leaves (Tambe et al., 2019).

In design and new product development, AI could optimize the process by supporting the developments of new features and functionalities (McKinsey Global AI Survey, 2019). For example, AI can screen alternative design ideas within the limits of budget and raw material needed, eliminate impossible ones, and prepare a preliminary list of alternatives for the human design team (Wilson & Daugherty, 2018).

At the actual product manufacturing or service delivery steps, AI utilization can depend on robots. Industrial robots are used in production since 1960s, starting first at General Motors (Kumar, 2010). However, utilization of more humanized robots to deliver a service and build a direct contact with customers is new. These robots, called as social robots, possess aspects like voice, identity and social abilities, and can behave according to the emotional feedback of the person served (Sandry, 2015; Young et al., 2009). They started to be used in service sectors like banks, restaurants or shopping malls, and expected to be more and more at work in the future, particularly for the elderly care and for the education of children with special needs like autism (Broadbent, 2017; İş Bankası, n.d.; Van Doorn et al., 2017).

The finance business unit can benefit AI at asset management, investment analysis, risk modeling, automation of the administrative tasks, follow up of payments and receivables, and at prevention of abuses and frauds (McKinsey Global AI Survey, 2019). The capability of AI to find patterns or relationships within seemingly unrelated data can effectively connect finance department to the other business processes (Davenport & Ronanki, 2018; Porter & Heppelmann, 2015).

Marketing is one of the business processes to benefit AI applications most (Chui et al., 2018; McKinsey Global AI Survey, 2020). AI brings highest return, when data can be collected and accumulated in high amount. First, the system needs to be fed with data to be more successful, and second managing such a high volume and variety of data is out of the capability of humans. Accordingly, AI benefit marketing especially when the customer base of the company is vast and when the contact with these customers are often, i.e. when a lot of customer and transaction data flows in, like retail, tourism, and financial services (Davenport et al., 2020).

In marketing, AI is used at strategic decisions such as segmentation and budget allocation, or at customer analytics such as prediction of buying propensity/churn potential/next or additional purchase, or at marketing mix actions such as pricing, promotion, and channel management (Davenport & Ronanki, 2018; McKinsey Global AI Survey, 2020). The utilization of AI in marketing helps both to increase revenues and decrease costs (McKinsey Global AI Survey, 2020).

One of the key benefits AI offers to marketing is within the very essence of marketing, namely understanding the needs and wants of a customer and finding people alike to form up groups of similar people within the society, i.e. segmenting (Kotler & Keller, 2016). In order to create value and assure strategic growth, companies shall provide their offer according to the needs and wants of customers (Hunt & Morgan, 1995) and segmentation narrows the focus down to a specific target, where needs will be matched best (Gilmore & Pine, 1997). Segmenting and accordingly realized targeting is the basis of strategic marketing as all following decisions in relation to product specifications, price offer, or communication shall refer to the achieved understanding (Kotler & Keller, 2016).

A well understanding in segmentation will match the demand of a specific customer with the optimum offer and support competitiveness (Kahn, 1998). Thus, the capability to profitably supply a specific demand, is discussed a lot in marketing under different concepts like database marketing, relationship marketing, interactive marketing, segments of one, mass customization, and personalization (Kara & Kaynak, 1997).

AI influences segmentation and targeting with the capabilities in collecting and analyzing data both for an individual consumer and for groups in the society. AI collects data at all forms related to the customer and the transaction before, during, and after the shopping (Davenport et al., 2020). This information could be valuable enough to replace long-term, high budgeted research activities and provide insights both to understand one person in specific as well as the whole society in aggregation (Wedel & Kannan, 2016). Then the marketing mix can be adjusted accordingly at different phases, from utilizing a specialized product visual at the online shop to differentiating a promotional campaign (Davenport & Ronanki, 2018; Kumar, Rajan, Venkatesan, & Lecinski, 2019).

In online shopping, segmentation and targeting are realized with recommendations. Online shopping recommendations, a powerful marketing tool to reply the needs and wants of a specific customer, are a very well working example of AI. Within the process, the system scans large amount of various data types, learns and readapts itself by each and every move of the shopper at the site, checks for patterns and similarities, and prepares an offer as an outcome.

2.2 Recommendations, a tool of Artificial Intelligence

2.2.1 Definition and importance in online shopping

Recommendations "elicit the interests or preferences of individual consumers for products, either explicitly or implicitly" (Xiao & Benbasat, 2007, p. 137). The main idea behind the recommendations is predicting the feedback of the person to the items not yet seen and showing the ones with the highest predicted rating (Adomavicius & Tuzhilin, 2005). Recommendations operate like the sales assistants at the physical shops, they assess consumer needs and tastes, and provide matching offers (Aksoy, Bloom, Lurie, & Cooil, 2006; Dabholkar & Sheng, 2012). They are capable to consider specific characteristics of the customer under focus, selections of other similar customers, or environmental factors such as location of the customer, time of the day, weather, upcoming specific events etc. (Adomavicius &Tuzhilin, 2005).

Recommendations are a major tool for companies, which are active in online world. They increase product views and conversions by a positive impact on awareness, i.e. by bringing the product into attention and distinction (Lee & Hosanagar, 2021). In offering substitute or complementary items, they build up an online network of products, where the value of a product is assessed within a multidimensional environment (Oestreicher-Singer, Libai, Sivan, Carmi, & Yassin, 2013). Overall, a mass customization capability is ensured leading to a higher customer loyalty (Schafer et al., 2001).

From the other perspective, recommendations benefit the customers as well. The digital world offers a very rich alternative potential, but also requires an extra effort from the customer (Chernev, 2003). The bounty of data can be overwhelming, create an information overload, and cause a cognitive complexity during shopping (Aggarwal & Vaidyanathan, 2003; Huffman & Kahn, 1998; Kahn, 2017; Lian & Lin, 2008). At this point, as a decision aid recommendations help to manage the cognitive difficulties, to smooth the shopping process, and to provide decision support (Häubl & Trifts, 2000).

Thus, Lamberton and Stephen (2016) stated that in regard of firm market intelligence and consumer decision support, recommendations build up a pioneering domain.

The importance of recommendations is growing hand in hand with the expansion of online shopping. Especially with the pandemic period conditions, accessibility, frequency, and variety of online shopping demonstrate splendid changes. Worldwide statistics show that retail e-commerce increased by 27.6% in 2020 compared to 2019 and the expectancy is that it will record a 49% increase in 2024 compared to 2020 (Statista, 2021). Specific for Turkey, compared to the year before, in 2020 online shopping increased 97% at out of food items, where the number of enterprises active online jumped up by 331% (Türkiye Sanayici ve İş İnsanları Derneği [TÜSİAD] Çok Kanallı Perakende Raporu, 2021; TÜSİAD Perakendenin Geleceği Raporu, 2021). This tendency is continuing in 2021 as well. Compared to the same period of 2020, e-commerce in Turkey increased by 75.6% within the first half of 2021 (Elektronik Ticaret Bilgi Sistemi [ETBIS], 2021). In fact, Turkey is the highest growing country in e-commerce during the pandemic and this growth is considered as having a 10-year progress leap (Statista, 2021; TÜSİAD Çok Kanallı Perakende Raporu, 2021; TÜSİAD Perakendenin Geleceği Raporu, 2021).

2.2.2 Classification

Structurally, recommendations can be studied according to data flow, design, and the implemented method details (Schafer et al., 2001; Xiao & Benbasat, 2007).

In terms of data flow, the choice on the out-flowing information concerns whether to include only one suggestion or a list of suggestions, and whether or not to show ratings/reviews specific for a person (Schafer et al., 2001). Regarding the inflowing information, the question concerns collecting data explicitly or implicitly (Adomavicius &Tuzhilin, 2005; Schafer et al., 2001). The explicit data has a higher quality and is more useful, but the implicit data can be more practical and non-intrusive (Adomavicius &Tuzhilin, 2005; Koren, Bell, & Volinsky, 2009). The explicit data collection is realized by asking the users to enter ratings, preferences, search keywords/features, comments etc.; where the implicit data collection depends on recording browsing history, items at shopping cart, purchase history, mobile usage, e-mail communication etc. (Adomavicius & Tuzhilin, 2005; Alibaba Privacy Policy, 2021; Amazon Privacy Notice, 2021; Schafer et al., 2001). New methodologies could even cover detection of the eye gaze and the facial expression of the customer (Jaiswal, Virmani, Sethi, De, & Roy, 2018). Another data source, which lately increases its importance, is social media networks (Zhao et. al, 2016). Some e-commerce platforms such as E-bay or Alibaba accept registration and entry through social media accounts. If the login is done with a social media account, it is taken granted that some data within this account can be shared with the e-commerce platform (Alibaba Privacy Policy, 2021).

In terms of design, the questions to be answered are the provided personalization level and delivery method, such as a push through e-mails or a pull through a link (Schafer et al., 2001; Wedel & Kannan, 2016).

In terms of methodology, the algorithmic calculations can have basically three different approaches, a content based one, a collaborative one, and a hybrid one (Adomavicius & Tuzhilin, 2005; Kim & Kim, 2018; Koren et al., 2009; Schafer et al., 2001; Tewari & Barman, 2018). The content-based recommendations identify products within the assortment according to their features and profile the very specific user according to her prior engagements (Kim & Kim, 2018; Koren et al., 2009; Schafer et al., 2001; Tewari & Barman, 2018). This method depends on keywords, hence it is generally realized on text-based retrievals and is useful for websites, news and printed material (Adomavicius & Tuzhilin, 2005; Isinkaye, Folajimi, & Ojokoh, 2015; Schafer et al., 2001). The main concern regarding content-based recommendations is that it can repeat itself within a limited circle of offers (McNee, Riedl, & Konstan, 2006; Tewari & Barman, 2018). On the other hand, collaborative filtering recommendations follows the behavior of the user under focus in order to find similar other users like her (Adomavicius & Tuzhilin, 2005; Kim & Kim, 2018; Koren et al., 2009; Schafer et al., 2001; Tewari & Barman, 2018). This approach can be done without a prior study and is very useful for subjects difficult to categorize such as music (Isinkaye et al., 2015; Koren et al., 2009). However, collaborative filtering experiences problems due to the cold start, i.e. the system cannot estimate how to start with a new user, for whom there is no clue, and with a new product, for which there is no accumulated knowledge of any customers (Adomavicius & Tuzhilin, 2005; Isinkaye et al., 2015; Koren et al., 2009; Tewari & Barman, 2018). Lastly, the two approaches can be utilized in a hybrid understanding to compensate the concerns and to benefit the strengths (Adomavicius & Tuzhilin, 2005; Isinkaye et al., 2015; Tewari & Barman, 2018). At Amazon for example, book recommendations include books, which are reviewed/commented/bought by other similar customers, recommended by the system according to the specific customer's previous engagement, listed by the editors, and stated at the best selling category (Schafer et al., 2001).

2.2.3 Success criteria

From the viewpoint of the company, a recommendation is successful when it achieves a high level of adoption and ensures post purchase satisfaction (Jiang, Shang, & Liu, 2010). This success shall naturally be influenced by the structure, design, and techniques used, but on the very basic level the system needs data to master. Data can create problems to the company both if it is too high and if it is too low. If customer and content data enlarges too much, the concern of scalability arises, in other words problems can be experienced in terms of system and time availability (Adomavicius & Tuzhilin, 2005; Schafer et al., 2001). Scalability gets an issue, as the online run of a recommendation system shall not be too long even if the data searched through expands very much (Jaiswal et al., 2018). Nevertheless, if the customer and content data remains too low, the system will not be able to understand the focused customer either. Low data availability could be in regard of all customers, namely sparsity, or specific for a new comer, namely, the cold start (Isinkaye et al., 2015; Tewari & Barman, 2018). In reality it is difficult to overcome the issues of sparsity and cold start, since there is a concentration of sold items, since each customer has a restricted pool of items bought, and since the users refrain rating or reviewing the content (Geuens, Coussement, & De

Bock, 2018; Tewari & Barman, 2018). These issues can lead the system to favor the items having more accumulated information, i.e. sold more or has more reviews/ratings (Adomavicius & Tuzhilin, 2005; Geuens et al., 2018).

From the viewpoint of the consumer, a recommendation is successful if it offers products, which the person herself would not consider at first, but would be very happy to purchase/use/consume when noticed (Reeves, Zeng, & Venjara, 2015). In other words, high consumer adoption is possible for a recommendation, when it sets a balance between offering accuracy, i.e. providing safe choices, and serendipity, i.e. new, original, and different alternatives (McNee et al., 2006; Sinha & Swearingen, 2001). The balance between accuracy and serendipity is also a concern of a recommendation list. Within such a list, each single one recommendation can be accurate, but the structure of the list itself can become redundant and dull, when all items are very similar to each other such as a list of only one author's books (Adomavicius & Tuzhilin, 2005; McNee et al., 2006).

This study takes the consumer perspective, accepts success of a recommendation as the customer's intention to adopt it, and compares this intention when the recommendation provider is AI or a Human advisor.

2.3 Adopting recommendations received from AI and Human advisors

To understand the consumer preference between AI and Human advisors, two different literature streams will be discussed. Both streams have specific strengths and weaknesses; combining them shall help to benefit from their assets while hindering the disadvantages.

The first literature stream compares two advice sources, i.e. AI and Human, and investigates consumer experience. However, it focuses on specific domains like driverless cars or AI utilization in medical treatments, and provides contradicting results (e.g. Castelo et al., 2019; Dietvorst et al., 2015; Dijkstra, 1999; Gill, 2020; Logg et al., 2019; Longoni et al., 2019; Luo et al., 2019; Senecal & Nantel, 2004). This stream does not offer answers concerning a preference between AI and Human advisors at an online shopping environment.

On the other hand, the second one questions the effectiveness of recommendations in online shopping and studies the impact of contextual factors. However, it considers AI as the sole provider of advice, hence there is no cue regarding a challenge with a Human advisor. In addition, this stream of literature centered heavily on the process to classify, understand and improve the accuracy of methods applied, and remained short in terms of questioning the consumer experience and reporting related feedback (Knijnenburg, Willemsen, Gantner, Soncu, & Newell, 2012; Qiu & Benbasat, 2010; Whang & Im, 2018; Yoon, Hostler, Guo, & Guimaraes, 2013). This could be a shared concern in high technology studies, as similarly, the literature on Internet of Things also focus on the development of technology (Harwood & Garry, 2017). However, it shall be noted that the consumer is focused on the experience rather than the algorithm (Hoffman & Novak, 2018).

2.3.1 Advice source comparison

The provider of a message can affect the feedback provided (Touré-Tillery & McGill, 2015). A literature stream investigates this feedback by comparing two different advice providers, Non-human and Human. Several concepts are used in the literature to describe the non-human advisor, e.g. algorithm, statistics, analysis, computer, software, robot etc.; in this study by investigating this literature stream all are grouped together under the umbrella term AI. Overall, this stream of literature shows contradicting results (Jussupow et al., 2020).

One vein of the literature supports the idea that humans are taken as the default advisor in comparison to AI (Dietvorst, 2016) and stresses algorithm aversion (Dietvorst et al., 2015). In other words, there is a general bias against AI (Luo et al., 2019). One of the reasons of algorithm aversion is that algorithms are considered as being open to mistakes, whereas the expectation from them is perfection (Dietvorst et al., 2015). Another algorithm deficiency is reported as the lack of ability to explain advice logic (Önkal et al., 2009; Yeomans et al., 2019). Customer feelings can play a role as well, as there is a possibility to hand over the decision responsibility to a human but not to a system (Promberger & Baron, 2006) and as perceived dissimilarity in decision making style and in humanness with a system can be irritating (Aksoy et al., 2006; Gai & Klesse, 2019; Nikolaeva & Sriram, 2006).

On the other hand, there are also studies showing algorithm appreciation. In predicting the weight, attractiveness, or song rank for example, algorithms are appreciated more than Human advisors (Logg et al., 2019). This appreciation can remain stable even if algorithms are considered as less knowledgeable and less trustworthy (Senecal & Nantel, 2004) and even if the comparison is against an average person, a group of others, friends, or a professional expert (Kennedy, Waggoner, & Ward, 2018; Sinha & Swearingen, 2001). The influential factors leading to algorithm appreciation are considered as consumer willingness to invest less effort (Dijkstra, 1999) and utilization of person specific data (Thurman, Moeller, Helberger, & Trilling, 2019).

According to a meta-analysis, out of 25 studies covered, 12 studies indicated aversion, four studies stated appreciation, and nine studies remained inconclusive, i.e. either showing no difference between algorithmic and human advice or reporting both aversion and appreciation at the same time (Jussupow et al., 2020).

The literature states that it is possible to manipulate algorithm adoption. One way to increase adoption is to offer the probability to experience AI capability in order to eliminate general bias (Luo et al., 2019). There are also domain specific solutions. Particularly, selecting objective areas, rephrasing the job as being more objective, and/or rephrasing the ability of AI mitigate algorithm aversion (Castelo et al., 2019). Another possibility is to include a human into the equation. When AI is used as a supporter to the human, i.e. as an augmenter, the aversion can be managed (Longoni et al., 2019). A similar way of including the human into the loop is to provide the person authority to correct the mistake of the algorithm, whereby very little control power can be sufficient to attenuate aversion (Dietvorst, Simmons, & Massey, 2018). This power grants the person the capability to affect the system (Hoffman, Novak, & Kang, 2016). Additionally AI can enjoy advantages in adoption, when it offers personalization, even mentioned by a small hint, or when it provides explanations concerning its working principles (Longoni et al., 2019; Whang & Im, 2018; Yeomans et. al, 2019).

Taking these manipulation tools into consideration, the vein of literature showing algorithm appreciation can be challenged. The studies of Senecal and Nantel (2004), Sinha and Swearingen (2001), and Thurman et al. (2019) stressed personalization, whereas Dijkstra (1999) and Kennedy et al. (2018) provided explanations of how the system is prepared and in what way it provides advices.

As within this stream of literature the gathered knowledge is not robust, the recommendation effectiveness literature, which provides greater accumulated information and a deeper focus on details, has been studied for further information.

2.3.2 Recommendation effectiveness

Surveys show that 91% of consumers want the retailer to provide well-prepared recommendations (Accenture Personalization Pulse Check, 2018). Companies like Amazon and Netflix report of owing 35% of their sales to recommendations (Love, 2014). In addition, literature supports recommendation effectiveness at online shopping (e.g. Banker & Khetani, 2019; Häubl & Trifts, 2000; Leavitt, 2006).

The factors behind recommendation effectiveness are studied by focusing on design, influencing factors, and consumer characteristics. Some of the studies considering design worked on the wording impact, particularly being passive such as others who bought this, also bought, or active such as buy also (Pöyry et al., 2017). Yet some others discussed availability and type of explanation (Wang, Qiu, Kim, & Benbasat, 2016; Zhang, & Curley, 2018); existence, ethnicity, and gender of an avatar (Qiu, & Benbasat, 2010; Wang, et al., 2016); and the number and scope of the questions stated to the customer (Kim & Kim, 2018; Wang, Luse, Townsend, & Mennecke, 2015). As well as the design of a specific recommendation, also the placement of it during different stages of purchasing funnel is assessed (Kumar et al., 2020; Pöyry, et. al., 2017; Zhang & Bockstedt, 2020). Results showed that adoption of a recommendation increases if the recommendation wording is not intrusive (Pöyry, et.al., 2017), if there are explanations regarding the logic (Wang et al., 2016; Zhang, & Curley, 2018), if there is a professionally perceived avatar (Wang et al., 2016), and if the ethnicities of the avatar and the customer match (Qiu & Benbasat, 2010).

In terms of the influencing factors, the adoption of recommendations is questioned under the impact of time pressure and changing social crowd (Kawaguchi, Uetake, & Watanabe, 2019). Other studies worked on the impacts of product release dates and product types (Helmers et al., 2019; Lee & Hosanagar, 2021; Pathak et al., 2010). The results showed that adoption of a recommendation increases when there is a low pressure of time and crowd (Kawaguchi et al., 2019) and when they are provided together with a newly released product (Helmers et al., 2019; Pathak et al., 2010).

Similarly, consumer characteristics are investigated to understand the recommendation adoption as well. The self-construal of the customer (Aljukhadar et al., 2017), cognitive overload experienced (Aljukhadar, Senecal, & Daoust, 2012), product knowledge (Yoon et al., 2013), variety within the population (Nikolaeva & Sriram, 2006), and similarity to the recommendation decision strategy are studied (Aksoy et al., 2006). Accordingly, the recommendation adoption is high when consumers have similar decision strategies with the recommendation (Aksoy et al., 2006), and experience a high cognitive overload (Aljukhadar et al., 2012).

A different branch of this literature worked to understand the potential negative effects of the recommendations. Impacts of biased recommendations are studied and possible protection methods are proposed (Xiao & Benbasat, 2015, 2018). Other studies focused on data in terms of amount, scope, and collection methods (Aguirre, Mahr, Grewal, De Ruyter, & Wetzels, 2015; Dabholkar & Sheng, 2012; Ghasemaghaei, 2020; Lee & Lee, 2009). Studies indicated that consumer reaction could be diverse. Results report that detailed questions can both lead to a high adoption of recommendations

(Dabholkar & Sheng, 2012; Ghasemaghaei, 2020) as well as a customer reactance (Aguirre et al., 2015; Lee & Lee, 2009).

Lastly, a more comprehensive view is taken to understand the macro impact of recommendations in terms of market diversity. The product network created by the recommendations (Oestreicher-Singer et al., 2013) is studied in regard of the items (Fong et al., 2019; Kim et al., 2010), of the buyers (Lee & Hosanagar, 2019), and of the competing providers (Li, Chen, & Raghunathan, 2018). Results show that at the aggregate level recommendations cause demand to focus on certain products, and total sales and diversity to fall (Fong et al., 2019; Kim et al., 2010; Lee & Hosanagar, 2019).

This research stream used mixed data collection methods such as online questionnaires (Kim & Kim, 2018), actual data scraped from e-commerce sites or get by field experiments (Helmers et al., 2019; Kawaguchi et al., 2019; Kumar et al., 2020; Lee & Hosanagar, 2019, 2021; Pathak et al., 2010; Pöyry, et.al., 2017), lab or online experiments (Aksoy et al., 2006; Qiu & Benbasat, 2010; Xiao & Benbasat, 2015; 2018; Yoon et al., 2013; Zhang & Curley, 2018), and simulation models (Kim et al., 2010; Li et al., 2018; Nikolaeva, & Sriram, 2006).

2.4 Theoretical framework

A recommendation is a technological artifact, whereas recommendation receiving is a communication, hence the subject needs to be studied both with technological and social aspects (Gefen, Karahanna, & Straub, 2003). Therefore, the technological framework utilized in the study is based on technology adoption and social relationship perspectives.

Technology adoption perspective is studied according to the Technology Acceptance Model (TAM). Considered that any person shopping online is a technology user, TAM offers a well-established way to give clues about behavioral outcomes (Koufaris, 2002). In relation, TAM has been utilized in several online customer behavior studies at the literature (e.g. Asosheha, Bagherpour, & Yahyapour, 2008; Baier & Stüber, 2010; Benbasat & Wang, 2005; Gefen, 2003; Koufaris, 2002).

Having a social relationship perspective is fundamental in terms of comparing AI and Human advisors. The very first criterion for intelligent machines is as being successful at a direct comparison with a human being, according to one of the pioneers of AI technology, Alan Turing (1950). In other words, the comparison against humans is the way that all AI technology started with. Within the study, this comparison is based on Imitation Game, Media Equation, and Uncanny Valley theories. Basically, Imitation Game and Media Equation theories state that AI can compete at the same track with humans. However, Uncanny Valley theory proposes that this feedback is not stable and can show discrepancies during the journey of technology.

2.4.1 Technology Acceptance Model

Since its introduction by Davis (1985), TAM has been the primary framework questioning technology adoption (Lee, Kozar, & Larsen, 2003; Marangunić & Granić, 2015).

To accept and internalize a new technology follows a basic framework built by reactions to use the technology, intentions to use it, and actual use of it (Venkatesh, Morris, Davis, & Davis, 2003). Within this understanding, TAM is based on the Theory of Reasoned Action (TRA) from Fishbein and Ajzen (1975), which defines the flow between belief-attitude-intention-behavior (Davis, Bagozzi, &Warshaw, 1989).

Whereas TRA appeals to various general domains, TAM focuses on technology adoption and explains acceptance of different technological novelties, specifically information technology (Davis, 1985, 1989; Davis et al., 1989; Marangunić & Granić, 2015; Venkatesh et al., 2003). TRA leaves the beliefs to be specified by the researcher and within TAM, these beliefs are set as perceived usefulness and perceived ease of use (Davis et al., 1989). Perceived usefulness construct corresponds to the belief whether the technology will benefit the outcome and perceived ease of use construct corresponds to the belief regarding which level of effort is needed to utilize that technology (Davis, 1989; Venkatesh & Davis, 2000). In other words, perceived usefulness and perceived ease of use can be seen as the benefit and the cost of adopting the technology (Davis, 1989).

TAM model proved itself at replications realized for several technological artifacts (Lee et al., 2003). Refinements of the model showed direct impact of beliefs on intention, hence within the latter versions of the model attitude have been omitted and the chain of belief-attitude-intention-behavior evolved to belief-intention-behavior (Baier & Stüber, 2010; Davis et al., 1989; Gefen et al., 2003; Koufaris, 2002; Marangunić & Granić, 2015; Venkatesh & Davis, 2000; Venkatesh, et al., 2003). By time, it had extensions as well. TAM2 elaborated the factors influencing perceived usefulness (Venkatesh & Davis, 2000); whereas UTAUT, Unified Theory of Acceptance and Use of Technology model integrated TAM with other technology adoption models (Venkatesh et al., 2003).

TAM is a useful model in marketing (Lee et al., 2003). The model can work out with several extensions influencing the basic two determinants of intention (Marangunić & Granić, 2015) and when used in marketing these extensions cover constructs like trust (Benbasat & Wang, 2005; Gefen et al., 2003), enjoyment (Koufaris, 2002) or playfulness (Asosheha et al., 2008). Adding social and emotional aspects to the model helps to overcome the criticism directed to TAM as being belief based only (Venkatesh, 1999). In other words, TAM relies on reasoned actions and rationality, but it needs to be supported with non-cognitive aspects as well (Gefen, 2003).

Particularly when utilized in online shopping studies, TAM is needed to be enhanced by adding emotional aspects to the cognitive ones (Komiak & Benbasat, 2006). Within this study, in order to cover social and emotional dimensions along with rationality, trust is used to extend TAM. Trust to the technology needs to be discussed since it is as crucial as functionality oriented usefulness and ease of use constructs (Benbasat & Wang, 2005; Gefen et al., 2003; Komiak & Benbasat, 2006; McKnight, Carter, Thatcher, & Clay, 2011). Trust helps to adapt the technology acceptance literature to a marketing environment and complete functionality with emotional aspects (e.g. Gefen et al., 2003; Koufaris, 2002; Van der Heijden, Verhagen & Creemers, 2003).

In addition to extending TAM, the study uses trust to evaluate the two advice sources within the same frame as well. Trust to technology is a derivative of the trust to a person and this trust relationship is similar to the one within an interpersonal context (Benbasat & Wang, 2005; Wang & Benbasat, 2008). In this sense, trust builds up the connection between the technology perspective and social perspective of the study.

2.4.2 Imitation Game Theory

At the Turing test, the machine shall be able to answer any sort of questions and pretend as if being a human (Turing, 1950). More specifically, if an interrogating person asks questions to two not seen entities, one being a human and the other one a machine, and cannot discriminate which one is a real human, then the machine is successful at imitation and has to be accepted as intelligent (Haenlein & Kaplan, 2019). Thus, Imitation Game describes the essence of machine intelligence within a direct comparison to a human.

Turing test keeps its actuality and this threshold is still accepted as a reliable criterion to be surpassed (Haenlein & Kaplan, 2019). The test expects AI to cover different dimensions of the human intelligence, as it should be able to realize any kind of a conversation. Although late developments of AI technology are powerful, the achieved capabilities as of today are still not sufficient for an artificial system to get into the human level (Kaplan & Haenlein, 2019). For example, visual, linguistic, and emotional intelligence dimensions are still in need of further development (Brynjolfsson &Mcafee, 2017).

In evaluating the feedback of a person to an AI technology, the fundamental assumption of Imitation Game is that the person does not see AI and thinks that a human is on the other side. However, another theory, Media Equation, proposes that even if the person gets into a face-to-face relationship with AI, she can still have a social connection with it, similar to a human.

2.4.3 Media Equation Theory

Media Equation theory states that people treat media equal to real life (Reeves & Nass, 1996). Hence, the relationship is unconsciously similar to the one observed within a social human-human interaction (Nass, Steuer, & Tauber, 1994; Reeves & Nass, 1996) and the conducts of a social communication such as personal space, attraction, group belonging etc. are applied as if in the real life and the related artifacts as if being actually alive (Griffin, 2006; Nass & Moon, 2000).

A derivation of the media equation theory is Computers Are Social Actors framework (CASA), which concentrates on digital technologies (Gambino, Fox, & Ratan, 2020). CASA states that people unconsciously build social bonds with computers (Nass et al., 1994) and heuristically react within well-known scenarios of the human-human social interaction (Nass & Moon, 2000). Reeves and Nass (1996) even propose that it is possible to replace the word human with the word computer within any psychological research paper about interaction, and to achieve the same output.

CASA paradigm has been demonstrated by a series of experiments. People perceived two identical computers as having different social identities depending on whether they use it or not during the experiment (Nass et al., 1994). For example, when criticizing the performance of the system, the computer used in the experiment is approached more politely compared to the one not used (Nass et al., 1994). On the other hand, when the software evaluates the participant, these critics are considered as being rougher when delivered by a computer not used in the experiment (Nass et al., 1994). Experiments also showed that gender stereotypes are associated to computers depending on the voice and the technology domain (Nass, Moon, & Green, 1997). Similarly, people act like a teammate with a computer by demonstrating high similarity perception, cooperation willingness, appreciation, and conformation (Nass, Fogg, & Moon, 1996). For example, cooperation willingness is observed as people invest more time and attention to help a specific computer reciprocal to a previous support received from it (Fogg & Nass, 1997).

According to the theory, no specific high technology attributors like voice recognition or emotional response evaluation are necessary to create such a social reaction; a simple text message on a black screen can be sufficient (Griffin, 2006; Reeves & Nass, 1996). For example, the reaction of being a teammate could be created by simply stressing dependency to each other (Nass et al., 1996). The whole series of CASA experiments were realized with 2-bit grayscale monitors without a sophisticated technology, and the computer never called itself as I (Nass et al., 1994). Meanwhile, within the period of more than two decades since CASA experiments, technology developed a lot and the relation with people evolved simultaneously becoming more intense, personal, and longitudinal (Gambino et al., 2020). Specifically in AI, enhanced personalized communication, addition of visual, speech and robotics technologies, and increased anthropomorphic cues can impact such a relationship.

Several studies support the expectation that CASA paradigm works with the contemporary technology. People with a high financial status expect a specialized level of treatment from a driverless car (Kim & McGill, 2018); social bonds are tight in terms of team building with machines (Sandry, 2015); and recommendation agents are evaluated like a person and considered within a social context (Benbasat & Wang, 2005; Qiu & Benbasat, 2010; Wang & Benbasat, 2008).

However, there are also studies demonstrating that the reaction to technology could be different from the one showed at a human-human relationship. At certain cases when moral rules have to be applied (Malle, Scheutz, Arnold, Voiklis, & Cusimano, 2015); when there is the need to tolerate a mistake (Dietvorst et al., 2015); and when a job replacement is realized (Granulo, Fuchs, & Puntoni, 2019; Waytz & Norton, 2014), AI faces a wall. It is noteworthy to understand how and why these specific cases arise. The answers may lie in the Uncanny Valley theory proposed to understand the reaction to robots (Mori, MacDorman, & Kageki, 2012).

2.4.4 Uncanny Valley Theory

In robot technology, it is important to uncover the feelings of humans when they receive service from robots, when robots accompany humans within a social context, or when they work together in a team (Kidd & Breazeal, 2008; Mende, Scott, van Doorn, Grewal, & Shanks, 2019; Rosenthal-von der Pütten, Krämer, Hoffmann, Sobieraj, & Eimler, 2013; Sandry, 2015; Van Doorn et al., 2017).

For these types of environments, the ultimate aim, especially pursued by engineers, is that the robot achieves a perfect reflection of human body in both appearance and functionality (Broadbent, 2017). Appearance and actions resembling humans shall persuade people to communicate with the robots and accept them within the physical human world (Phillips, Zhao, Ullman, & Malle, 2018). Additionally, people evaluate the same technology being in a more humanized appearance as stronger, higher in capability, more enjoyable, and more reliable (Mann, MacDonald, Kuo, Li, & Broadbent, 2015).

However, Uncanny Valley theory objects to this understanding and states that the reactions to the changes at a robot outlook do not follow a linear line, in other words it cannot be said that the more a robot looks like a human, the more positive reactions it receives (Mori et al., 2012). As presented at Figure 1, the theory states that at the beginning, any additional humanized specification on the robot adds up to the affinity level for the humans. However, at a certain level, where the robot is not as a machine any more but could not be perceived as a human at all measures either, the affinity suddenly drops deeply and the robot is thought to be eerie. After this lowest point of affinity, when the robot increases its similarity to humans, the reactions start to recover again. The phase where the positive reaction loses its momentum, first turns to the opposite direction, and then recovers again is called as the Uncanny Valley (Mori et al., 2012).

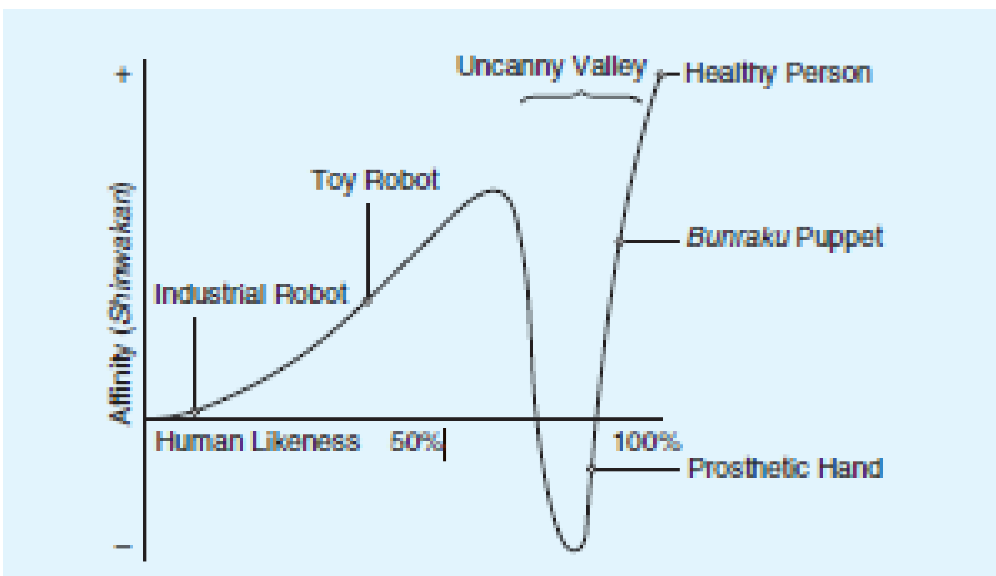


Figure 1. Uncanny Valley theory
(Mori et al., 2012)

The most important appearance clues in a robot are surface aspects such as skin, hair and gender, and body parts such as torso, arms and fingers (Phillips et al., 2018). On top of appearance, movement capacity plays an important role by deepening the impact of fall and rise at the Uncanny Valley (Mori et al., 2012). The discomfort experienced could be caused by the not well-managed physical distance or the non-awareness of being touched as well (Scheeff, Pinto, Rahardja, Snibbe, & Tow, 2002).

According to the Uncanny Valley theory, the advice for the robot technology is to stay at the positively increasing part of the relationship between human likeness and affinity level and avoid entering the valley (Mori et al., 2012). In other words, a total proximity to humans shall not be aimed. On top of the risk to fall into Uncanny Valley, focusing on how a robot should be designed to resemble a human body exactly, causes human specific physical boundaries to be reflected at robots as well (Luria et al., 2019).

CHAPTER 3

DEVELOPMENT OF THE RESEARCH MODEL

The research takes recommendations at online shopping as an everyday met example of AI and questions the feedback to AI through the adoption of recommendation. Following the theories of Imitation Game and CASA, AI is compared with a Human advisor and following the theory of Uncanny Valley, this comparison is challenged by empowering AI gradually.

The observed preference differences between the two advice sources will then be analyzed within the theory of TAM in order to understand the mechanism behind. The TAM model is extended with cognitive and emotional trust in addition to perceived usefulness, perceived ease of use, and intention to adopt the recommendation to cover cognitive, emotional, and social aspects.

3.1 Constructs

3.1.1 Cognitive trust and emotional trust

Trust is established where the trustee is expected to act non-opportunistic (Gefen et al., 2003), therefore it increases relationship commitment and cooperation between the parties and has a strong impact in marketing (Morgan & Hunt, 1994).

Concerning technology, trust can be studied as faith and dependence in technology in general, being dispositional; as trust to the class or the environment of the technology, being institutional; and as trust to a specific technological artifact, being interpersonal (McKnight, Choudhury, & Kacmar, 2002; McKnight et al., 2011). The literature mostly covers studies within the first two areas, however trust is an important element concerning a relationship with a specific technological artifact, and hence the interpersonal trust domain shall be considered as well (Benbasat & Wang, 2005; McKnight et al., 2002; McKnight et al., 2011). Trust to a technological artifact contributes to the intention and actual use of it (Wang et al., 2016; Zhang & Curley, 2018) and is a beneficial extension of TAM (Benbasat & Wang, 2005; Gefen et al., 2003).

In terms of online shopping, the customer experiences risks due to a medium existing in between the relationship with the seller (Bauman & Bachmann, 2017). Hence, in online shopping trust is more essential than in traditional shopping (Van der Heijden et al., 2003). Nevertheless, it is at the same time much more complex to build compared to the off line shopping environments (Bauman & Bachmann, 2017; Jarvenpaa, Tractinsky, & Vitale, 2000). One of the solutions for this complexity lies in recommendations, as they can build up trust by providing convenient proposals and considering the benefit of the consumer (Komiak & Benbasat, 2006; Wang et al., 2015). In other words, they provide help to the online shopper, who is facing the risk of low quality decisions in a cluttered world (Dabrowski & Acton, 2013).

Shoppers ask for both utilitarian and emotional aspects (Koufaris, 2002), therefore in addition to functioning as a decision support tool, recommendations shall also fulfill social relationship needs (Komiak & Benbasat, 2004). Trust is a social construct (Gefen et al., 2003; Lewis & Weigert, 1985), and recommendation agents capable to act as social actors, shall assure trust in this direction as well (Gambino et al., 2020). Accordingly, by taking recommendations both as a functional decision tool and as a social relationship partner, this study uses two different dimensions of trust stated in the literature, namely cognitive trust and emotional trust (Komiak & Benbasat, 2006; McKnight et al., 2011). Each one dimension of trust is insufficient alone to explain the end decision and only by evaluating both in a combination shall provide a full comprehension of technology adoption and trust relationship (Komiak & Benbasat, 2006).

Cognitive trust depends on the rationality and reasoning of the person that the trustee possesses the crucial valuable specialties (Komiak & Benbasat, 2004; McKnight & Chervany, 2001). It has a multidimensional nature (Gefen, 2002; McKnight et al., 2002) and the dimensions are ability, predictability/integrity, and benevolence (McKnight & Chervany, 2001; Mcknight et al., 2011). The dimensions stated for the interpersonal context show a similar structure in respect of a technological artifact as well, within the technological realm the dimensions can be named as competence or ability, integrity, and benevolence (Benbasat & Wang, 2005; Gefen, 2002; McKnight & Chervany, 2001; Mcknight et al., 2011; Ridings, Gefen, & Arinze, 2002; Wang & Benbasat, 2008).

Whereas the dimensions build together the construct of cognitive trust, it is also crucial to have a separated understanding of each (Gefen, 2002; McKnight et al., 2002; Zhang & Curley, 2018). In regard of recommendations for example, each dimension can impact different stages of shopping, where ability is more important at window shopping to find the best option, integrity and benevolence come forward at purchase intention by providing fairness and goodwill (Gefen, 2002; Komiak & Benbasat, 2006).

Ability: Ability means having the capability and power to fulfill the expectancy and deliver the request (Gefen, 2002**;** McKnight & Chervany, 2001; McKnight et al., 2011).

For cognitive trust to AI, ability is a game changing dimension. People expect perfection from AI technology (Dietvorst et al., 2015; Dietvorst & Bharti, 2019). Even experiments with children show that they, who are open to new technologies, have difficulties building up trust to robots making mistakes (Geiskkovitch, Thiessen, Young, & Glenwright, 2019). As AI technologies spread out to different domains, ability expectancies can differ accordingly. For example, whereas functional safety is the most crucial aspect for an autonomous vehicle (Hengstler et al., 2016), accuracy is essential for an online shopping recommendation (Komiak & Benbasat, 2006; Leavitt, 2006; Schafer et al., 2001).

Integrity: Integrity is the belief regarding the character of the trustee to act in ethical boundaries (McKnight & Chervany, 2001; Wang & Benbasat, 2008). In a more detail, it states that the trustee will be loyal to promises, has the willingness to act proper within the relationship, will follow the rules of conduct, and remain consistent (Gefen, 2002**;** McKnight et al., 2011).

Regarding AI, integrity offers trust in development and utilization of the technology with good intention; in parallel, integrity at recommendations shall ask for not applying biases and not restricting the consumer free will (André et al., 2018; Komiak & Benbasat, 2004, 2006). Additionally, collected data for recommendations shall be protected, will not be used for purposes other than providing an offer, and will not be shared with third parties (Kim & Kim, 2018; Mazurek & Małagocka, 2019).

Benevolence: Benevolence means carrying a positive attitude within the relationship (Ridings et al., 2002), genuinely putting the benefit of the other party in priority (McKnight et al., 2002), and not acting by opportunistic steps or by self-interest motivation (McKnight & Chervany, 2001). Concerning recommendations, it means acting with goodwill in the best interest of the consumer (Benbasat & Wang, 2005; Wang & Benbasat, 2008).

On the other hand, emotions are an important part of trust as well (Johnson & Grayson, 2005; Komiak & Benbasat, 2006; Lewis & Weigert, 1985; McKnight & Chervany, 2001; Wang et al. 2016). In online shopping it is important to evaluate emotional aspects as well as cognitive ones (Cyr, Head, & Ivanov, 2009; Koufaris, 2002) but in recommendation literature studies related to consumers' feelings are hard to find (Komiak & Benbasat, 2004, 2006; Martínez-López et al., 2015).

In terms of recommendations, emotional trust refers to how much a person feels intact and pleased in adopting the advice received from the specific source (Komiak & Benbasat, 2006). It is an overall feeling to depend to the other party (McKnight & Chervany, 2001). Whereas cognitive trust is built with the valuable specialties of the trustee (Komiak & Benbasat, 2004; McKnight & Chervany, 2001), emotional trust keeps the trusting party viewpoint (Komiak & Benbasat, 2006). Additionally, emotional trust does not have to be based on rationality and is not realized in an analytical piecemeal process (Komiak & Benbasat, 2006).

Recommendations help the decision maker by either downsizing a vast variety of an assortment to a manageable number or by choosing the best offer on behalf of the customer directly (Komiak & Benbasat, 2006). Hence, with the enhancing variety within the assortments offered in online shopping and developing recommendation technologies, the expected dependency of a typical consumer to recommendations shall increase and the importance of emotional trust to the recommendation source shall escalate.

3.1.2 Perceived usefulness

Perceived usefulness is the belief whether the results are improved thanks to the utilization of the system in question (Davis, 1989). It is an indicator of intention to adopt the technology and keeps its significance over lengthened utilization time (Venkatesh et al., 2003).

Similarly, in order to adopt a recommendation, usefulness is essential, in other words a recommendation shall propose the optimum alternatives among a vast assortment within a short period (Asosheha et al., 2008). To be optimum, the proposed alternative shall provide accuracy (Leavitt, 2006; Schafer et al., 2001) and ensure diversification at the same time (Adomavicius & Tuzhilin, 2005; Geuens et al., 2018).

3.1.3 Perceived ease of use

Perceived ease of use is the foreseen effort to use the system in order to receive the benefit (Davis, 1989). The acceptance of technology increases when a tool gets easier (Davis, 1989) because customers do not want to add on new and unknown challenges to the daily life (Hoffman & Novak, 2018). When a technological artifact is difficult to use, the user can feel incompetent, and hence refuse the product, delay the purchase, choose a simple model, or abandon utilization (Mick & Fournier, 1998).

In terms of recommendations, the rule based recommendations asking the consumer for their needs and wants (Aggarwal & Vaidyanathan, 2003) differ from the more contemporary ones working at the background (Kumar et al., 2019). At the contemporary recommendations consumer receives recommendations without any direct input, however understanding the operational logic and the targets of the technology is as important as the utilization interface (Hengstler et al., 2016).

3.1.4 Intention to adopt

At its introduction, TAM focused on organizational settings and researched computer acceptance as the sought behavioral result (Davis et al., 1989). With the technology diversifying and diffusing into personal lives, TAM studies expanded to systems like desktop applications, Internet, e-mail etc., whereas acceptance has still been assessed as the targeted end result of the process and mostly judged by the actual utilization of the technology in question (Lee et al., 2003). In terms of recommendations, acceptance is considered as the intention to adopt the received advice (Komiak & Benbasat, 2006; Venkatesh et al., 2003). Accordingly, the intention to adopt the recommendation would mean that the customer is ready to use the advice in decision making.

3.2 Hypotheses

3.2.1 Study 1: AI vs. Human - advisor differentiation in adopting the advice (see Figure 2)

H1: Human advice will be preferred over AI advice

In contrary to Human advisor, AI meets a resistance, in other words an aversion (Castelo et al., 2019; Dietvorst et al., 2015). This aversion is observed both when it provides recommendations in regard of forecasting or predicting (Dietvorst et al., 2015; Önkal et al., 2009; Yeomans et al., 2019), as well as when it performs a service like at autonomous driving, medical assistance, or call center support (Hengstler et al., 2016; Longoni et al., 2019; Luo et al., 2019; Promberger & Baron, 2006). Similarly in online shopping, when recommendations are stated to be based on other user's tastes, such as purchases, comments or likes, they are appreciated more compared to the ones stated as being based on the product category (Gai & Klesse, 2019). In other words, although at both of the cases it is the system, which prepares the offer, the hint on the people changes the scope.

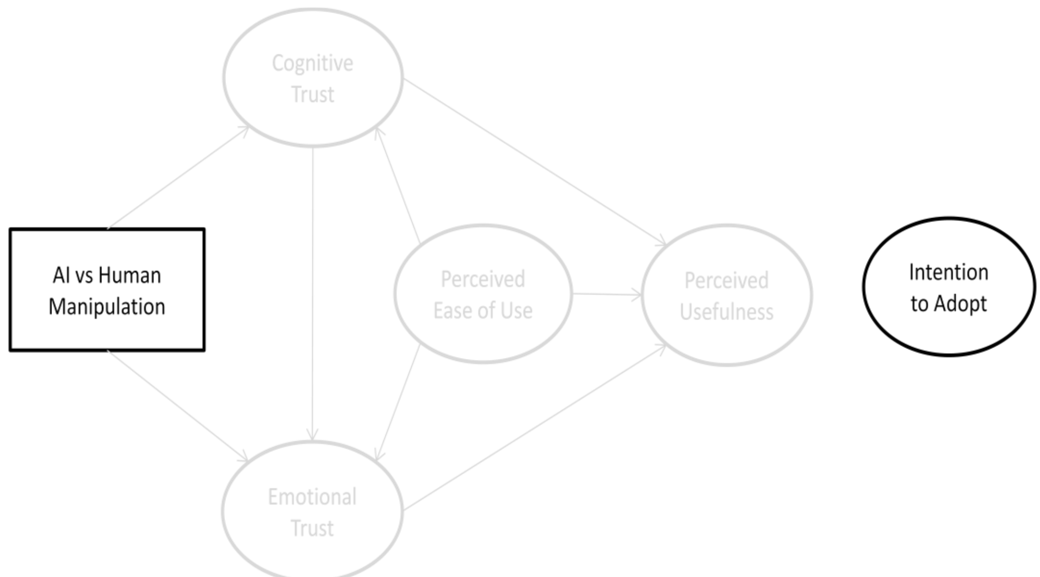


Figure 2. Hypotheses structure for study 1

Algorithm aversion is also active at professional level. Companies utilizing AI depended technologies avoid using the term AI; since they consider it to be scary, confusing, and open to misunderstanding, therefore they prefer words like autonomous, automated or assistant (Hengstler et al., 2016). When the company is a digital born one and depends solely on AI technology, then it is mentioned together with an emphasis on the human touch (Lake, 2018; Stitch Fix, n.d.). Company managers foresee that algorithm aversion will be such high that in future customers would prefer to realize extra payment in order to be served by a human (Brock & Von Wangenheim, 2019). Similarly, doctors prefer to ask for advice from their colleagues instead of AI when they have to decide on difficult operations for their patients (Yang et al., 2016).

First reason to avoid an algorithm and prefer a human advice is due to cognitive evaluations. The capability of AI is doubted, especially after observing an imperfection (Dietvorst et al., 2015). As the advices from humans are prone to more and bigger mistakes, the cost to avoid the algorithm is high, however the idea is that humans are able to learn from the mistakes, develop themselves, and catch outliners (Dietvorst et al., 2015). There are also prejudices against AI competence in general (Luo et al., 2019) and for subjective domains in specific (Castelo et al., 2019). In addition, it is considered that AI does not have the possibility to provide an explanation regarding the logic of the advice (Önkal et al., 2009; Yeomans et al., 2019).

Second, there are feelings arising. Humans are accepted as the default advisor and owner of the power, so AI is the second one compared to the default advisor (Dietvorst, 2016). When in front of AI, people can experience estrangement, so that for example a win at a videogame after the help from an avatar can not be owned by the player (Kim, Chen, & Zhang, 2016). In some other cases, AI advices can increase anxiety, since the responsibility of the decision cannot be handed over (Promberger & Baron, 2006). However, Human advisors like doctors take the accountability of difficult decisions. Lastly, between the two parts of the recommendation process, receiver and provider, similarity is important for persuasion (Aksoy et al., 2006). When a recommendation is received from a dissimilar source, it is downgraded because of the missing similar taste perception (Gai & Klesse, 2019; Nikolaeva & Sriram, 2006). The potential to assure social presence and similarity in humanness are different for AI and

Human advisors as well (Aksoy et al., 2006; Fulk, Steinfield, Schmitz, & Power, 1987; Gefen & Straub, 2004; Kumar & Benbasat, 2006).

Relying on the algorithm aversion vein of the literature, this study posits that the recommendation provided by a Human advisor will face a higher intention to adopt compared to the one provided by AI. Within the study, the recommendation received covers an apparel and fashion item, i.e. open to subjective evaluation where AI is considered as low in capability (Castelo et al., 2019). Specifically in this domain, the Human advisor, i.e. the designer in this case, would be accepted as the default advisor for style (Dietvorst, 2016) and would be considered as rating higher in humanness and social presence (Aksoy et al., 2006; Fulk et al., 1987; Gefen & Straub, 2004; Kumar & Benbasat, 2006). In addition, the manipulation at the study specifically refrained utilization of any wording to evoke a mitigation impact such as personalization (Longoni et al., 2019), explanation (Yeomans et. al, 2019), and control possibility of the process (Dietvorst et al., 2018).

H2: The preference of Human advice over AI advice shall differ according to the recommendation type

A stepwise empowerment of AI, envisioned as recommendations starting with a basic one and then scaling up to an upsell option, a cross sell combination offer, and lastly to a product designed by the advisor directly, is utilized within the study. Accordingly, the study posits that the capability of AI shall be questioned more and the gap between AI and Human shall deepen, when the recommendations gradually pass from a basic recommendation up to a design offer.

Recommendations could be basic, i.e. they can offer a substitute item, which is in the same product category and comparable to the initial product (Helmers et al., 2019).

On the other hand, upsell possibilities relate to proposing a higher price based product, being a bigger package or a higher quality (Bose & Chen, 2009). At the next level, the recommendation can ask for a divergence from the initial starting point or increase purchase amount by offering complementary products from a different product category in addition (Helmers et al., 2019). Whereas basic recommendations use terms such as you may also like, cross sell recommendations use terms such as how to wear it (Helmers et al., 2019). Lastly, a recommendation regarding a design directly realized by the advisor shall be a unique product and have a higher price accordingly. Changes within the product category and increases at the purchase amount shall enhance questions concerning competency in subjective evaluation and creativity. However, AI is believed to be only successful at subjects, which are measurable, objective, and number oriented (Castelo et al., 2019).

Huang and Rust (2018) propose a similar stepwise understanding in terms of job allocations between AI and human employees. As creativity, experiential thinking, social interaction, and emotional feedback are required at the higher levels of intelligence, AI shall follow the ordinal progress of mechanical, analytical, intuitive, and empathetic jobs (Huang & Rust, 2018). Accordingly, at the so-called Feeling Economy, AI shall take place at the basic levels and leave upper level stages to humans (Huang et al., 2019). Especially when creativity is concerned, although news often arise regarding the activities of AI in art such as paintings (Max-Planck-Gesellschaft, 2020), the literature is suspicious about AI performance (Kaplan & Haenlein, 2020).

Additional to creativity, the progress presented at the study creates a more complicated advice at each step. A basic recommendation shall depend on understanding the need, finding similar offers from the assortment, and predicting the feedback. An upsell recommendation, on top of covering these steps, should go one step further and provide an additional benefit. Also, an upsell offer is not directly related to the purchase or view history of the shopper and hence is more difficult to realize (Bose & Chen, 2009). Then the next step, cross sell, should again understand the basic need and dive into the assortment, but this time with the purpose to offer a diversified additional item. Hence, a cross sell recommendation needs to be able to expand and elaborate the need. Lastly, design is a difficult act by itself since it corresponds not to finding an item from an already available assortment but composing the offer from scratch. AI is believed to be an extension of advanced statistics, to take the standard, the majority, or the average as the norm, and to depend on rules (Castelo et al., 2019; Longoni et al., 2019). If the case on hand carries high ambiguity and few rules, AI is disregarded (Dietvorst & Bharti, 2019). Hence, a fashion recommendation starting from a replacement with an alternative product and then going through combination proposals up to a design offer, shall let AI to lose more and more at each step.

Lastly, AI effect states that although considered as a very high technology at introduction, any AI progress easily and quickly can become ordinary by reaching masses and being a tool of everyday life (Haenlein & Kaplan, 2019; Kaplan & Haenlein, 2019). In other words, when seen and utilized often, an AI tool is considered as normal and performing an easy task. In practice, basic recommendations are very common at e-commerce platforms, upsell and cross sell are also available but observed less (Bose & Chen, 2009; Zhang & Bockstedt, 2020) and an offer of a product designed by AI at an online shopping site is very seldom. Hence, for basic recommendations AI effect shall be at work, i.e. consumers shall be used to basic product recommendations, shall evaluate them as easy and ordinary, and shall consider AI as being capable. However, with decreasing utilization of upsell, cross sell, and design offers, AI shall be taken as less adequate, since these steps need a higher intelligence, in other words a more miraculous performance of AI.

3.2.2 Study 2: AI vs. Human - advisor differentiation in revealing cognitive and emotional trust (see Figure 3)

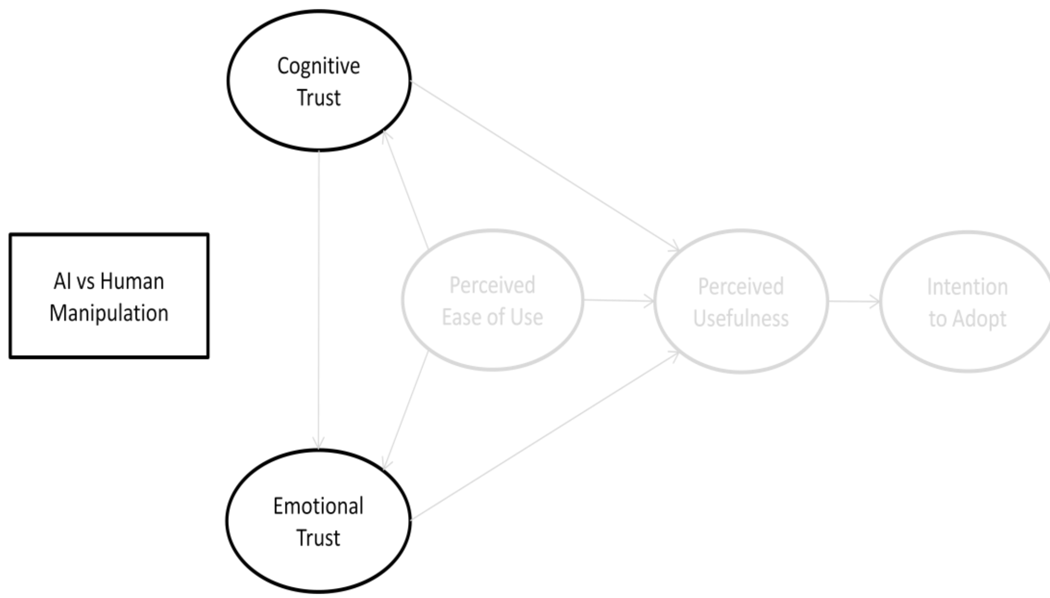


Figure 3. Hypotheses structure for study 2

H3a: Human advisor is credited with higher cognitive trust compared to AI

H3b: The difference in cognitive trust credited to AI and Human advisors shall be influenced by the recommendation type

H4a: Human advisor is credited with higher emotional trust compared to AI

H4b: The difference in emotional trust credited to AI and Human advisors shall be influenced by the recommendation type

In general, people trust humans more than AI (Castelo et al., 2019; Promberger & Baron, 2006; Yeomans et al., 2019). Accordingly, trust to AI increases with the addition of some anthropomorphism aspects, in other words when it approaches to humanness (Waytz et al., 2014).

AI and Human advisors can be compared in terms of the cognitive evaluation of the valuable specialties owned, i.e. ability, integrity, and benevolence (Komiak & Benbasat, 2004; McKnight & Chervany, 2001). Regarding ability component, people have a solid understanding about the skill domains of AI and a general negative bias (Castelo et al., 2019; Dietvorst et al., 2015; Luo et al., 2019). In addition, even if the same not accurate recommendation is received from both AI and Human advisors, AI is punished more as the expectancy from AI covers perfection (Dietvorst et al., 2015; Dietvorst & Bharti, 2019).

In addition, although AI can have a social role according to CASA (Nass et al., 1994), the default owner of the credits of integrity and benevolence is the human (Benbasat & Wang, 2005; Dietvorst, 2016). Integrity asks being free of bias and manipulation, and having good intention (André et al., 2018; Komiak & Benbasat, 2004; Komiak & Benbasat, 2006), whereas benevolence needs a positive attitude and not acting opportunistic (McKnight & Chervany, 2001; McKnight et al., 2002). However the hype around AI and the negative news arising, such as Amazon discriminating against women applicants, Chinese social credit system watching the public, or deep fake acts causing the reality to be questioned, are challenging the believes in integrity and benevolence of AI (Dastin, 2018; Mirsky & Lee, 2021; Xu & Xiao, 2018).

Only cognitive aspects are not enough to build trust, also feelings mix in (Cyr et al., 2009; Johnson & Grayson, 2005; Komiak & Benbasat, 2006; Lewis & Weigert, 1985; McKnight & Chervany, 2001; Wang et al. 2016). However, AI is considered as being incapable in terms of emotions (Longoni, Fradkin, Cian, & Pennycook, 2021) and hence an emotional relationship is easier to build with a human compared to AI.

Emotional trust considers an overall relying to the other party (McKnight & Chervany, 2001). AI is a new technology and develops very fast. Although meeting an AI technology artifact everyday with many examples, people have trouble to absorb this technology (e.g. Castelo et al., 2019; Dietvorst et al., 2015; Longoni et al., 2019). As a result, they take AI to be scary (Hengstler et al., 2016), and have concerns in leaving themselves to the hands of it.

In addition, trust asks for a social relationship at recommendation receiving (Gefen et al., 2003**;** Komiak & Benbasat, 2004; Lewis & Weigert, 1985) and humans can realize this social relationship in a more familiar way and with a higher social presence (Gefen et al., 2003; Gefen & Straub, 2004). Specific for online shopping, whereas a Human advisor would seem like a direct contact, an AI advisor would be an intermediary between the buyer and seller, and hence increase the overall perceived risk (Bauman & Bachmann, 2017). Therefore the emotional trust on AI shall be lower compared to a Human advisor.

Lastly, both for cognitive and emotional dimensions, the scaling up process realized within the study shall increase the trust gap between AI and Human advisors. The doubts discussed above shall get more intense at each step, where the offer scope is enhancing. In other words at more subjective and complex offers, ability component will be questioned more, lack of integrity and benevolence will seem more threatening, and surrendering with an overall reliance will be more difficult.

3.2.3 Study 3: AI vs. Human - advisor differentiation in evaluating recommendation usefulness and ease of use (see Figure 4)

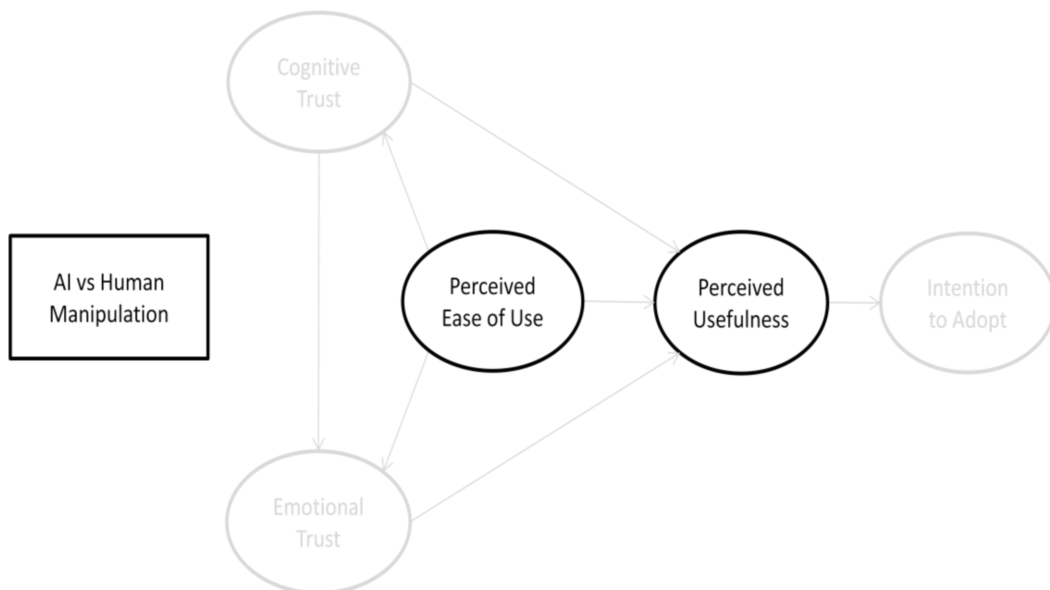


Figure 4. Hypotheses structure for study 3

H5a: Perceived ease of use in getting a recommendation is higher when the recommendation source is Human

H5b: The difference of perceived ease of use in getting a recommendation between AI and Human advisors shall be influenced by the recommendation type

H6a: Perceived usefulness of a recommendation is higher when the recommendation source is Human

H6b: The difference of perceived usefulness of a recommendation between AI and Human advisors shall be influenced by the recommendation type

The contemporary recommendations are received automatically during online shopping (Kumar et al., 2019) and the shopper does not provide any input like at the rule based recommendations, where needs or wants shall be indicated to the system (Aggarwal & Vaidyanathan, 2003). Hence, within the daily utilization, learning and utilizing recommendations do not ask for an extra effort. However, the concern about perceived ease of use also lies in clarity and understandability of the process (Koufaris, 2002; Lee & Lee, 2009).

One of the concerns regarding AI, especially machine learning and deep learning mechanisms, is the black box mentality, where let alone the ordinary users, even the developers of a system could not explain the logic behind an output (Haenlein & Kaplan, 2019). Therefore, it is not easy to understand AI technology, especially the more advanced forms of it (Kaplan & Haenlein, 2020). However with a Human advisor, similarity in humanness shall lead to the perception of having a similar rationality, thereby making the recommendation getting process more understandable as well (Aksoy et al., 2006). In addition, whereas an explanation could be asked from a Human advisor, there is no possibility to question AI about the logic (Önkal et al., 2009; Yeomans et al., 2019). Hence, the advice from a human shall be perceived as easier to understand, i.e. easier to use, and the gap with AI shall increase when a recommendation becomes more advanced, that is more complicated in logic.

Perceived usefulness of a recommendation refers to the support provided to increase shopping performance, productivity, and effectiveness (Koufaris, 2002; Lee and Lee, 2009). The subject of the study is fashion; therefore the shopping performance or the effectiveness of the recommendation received can not be measured objectively, but would more depend on tastes. As AI is considered to be weak in not measurable domains (Castelo et al., 2019) and as the taste from a Human advisor shall be perceived as having more similarity with the person receiving the advice (Gai & Klesse, 2019;

Nikolaeva & Sriram, 2006), the recommendation from a Human advisor shall be evaluated as more useful. Additionally, as at the more advanced levels of recommendation, i.e. proceeding from a basic level to the design, shopping effectivity shall get more difficult to reach and the difference between AI and Human advisors shall widen.

3.2.4 Study 4: AI vs. Human - expanded TAM model (see Figure 5)

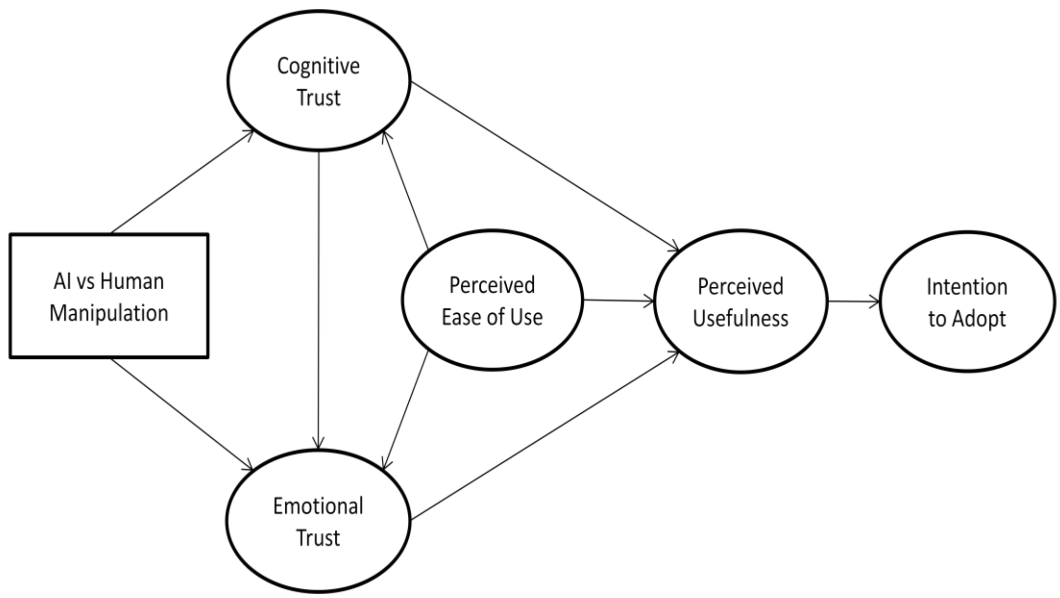


Figure 5. Hypotheses structure for study 4

H7: Cognitive trust to the recommendation source positively influences emotional trust to the recommendation source

Whereas cognitive trust is related to the belief concerning the characteristics of the trustee (Komiak & Benbasat, 2004; McKnight & Chervany, 2001), emotional trust is an attitude (Komiak & Benbasat, 2006) and according to TRA beliefs impact attitude (Fishbein & Ajzen, 1975).

Being more specific, cognitive aspects based and developed on the received information help to develop an opinion and raise emotions (Wang et al., 2016). In recommendations as well, the beliefs regarding ability, integrity, and benevolence of the recommendation source influence the overall relying (McKnight & Chervany, 2001). If for example, a person has believes that the recommendation source informs very well about the offer, she would rationally decide in being secured, and then feel comfortable to rely on that source (Komiak & Benbasat, 2004).

H8: Cognitive trust to the recommendation source positively influences perceived usefulness of the recommendation received

Cognitive trust refers to a reasoning of the person that the advisor possesses crucial valuable specialties (Komiak & Benbasat, 2004; McKnight & Chervany, 2001). If the advisor is believed to possess the characteristics of ability, integrity and benevolence, the recommendation received from this advisor shall be considered accurate, not biased and carrying good will, in other words as effective and fulfilling the need at best options (Benbasat & Wang, 2005; Gefen et al., 2003; Wang et al., 2016).

H9: Emotional trust to the recommendation source positively influences the perceived usefulness of the recommendation received

Trust gives clues for future relationships (Gefen et al., 2003). In other words, the higher the trust to the advisor, the more willingness is shown to sustain the relationship. However, emotional trust is an attitude and not based on rationality (Komiak & Benbasat, 2004; Komiak & Benbasat, 2006) and the person would not be able to explain this intention for future. In this case, the actual recommendation can be used for help.

When the overall dependence, i.e. emotional trust is high, the assessment of a higher perceived usefulness shall provide a justification. On the other hand, taking a negative perspective, when the mind of the shopper is not cleared of any concerns felt to the source of the advice, that is when emotional trust is low, she could not concentrate on the usefulness of the recommendation and could not evaluate it free from the emotional state. As no explanation can be provided rationally, the easiest way is to put any blame on the usefulness of the technology and evaluate the recommendation as less useful.

H10: Perceived ease of use in getting a recommendation positively influences cognitive trust to the recommendation source

H11: Perceived ease of use in getting a recommendation positively influences emotional trust to the recommendation source

Perceived ease of use can be taken as clarity and understandability of the process for the contemporary recommendations delivered at online shopping (Koufaris, 2002; Lee & Lee, 2009). Analytically evaluating a recommendation process as being clear and understanding the process, increase cognitive trust to the advisor (Benbasat & Wang, 2005; Gefen et al., 2003). Accordingly, explanations about the reasoning of a recommendation increase positive feedback at the receivers (Wang et al., 2016; Yeomans et. al, 2019; Zhang & Curley, 2018).

In addition, a transparent recommendation process will show the shopper that she is cared for and that the advisor is putting her best within this relationship, in other words deserves emotional trust (Gefen et al., 2003). On the other hand, if people could not understand the logic of a recommendation, they can get confused, anxious, frightened and doubtful, all of which would lead to a diminishing reliance (Hengstler et al., 2016).

H12: Perceived ease of use in getting a recommendation positively influences perceived usefulness of the recommendation

H13: Perceived usefulness of the recommendation positively influences the intention to adopt the recommendation

TAM models use perceived ease of use and perceived usefulness to predict and explain behavioral intention. Although being challenged with different technological artifacts, the model remained solid since its introduction (Lee et al., 2003).

One of the proposals of TAM is the relationship between perceived ease of use and perceived usefulness. Perceived ease of use influences perceived usefulness, as the less effort needed to use the system the more useful it is considered (Benbasat & Wang, 2005; Gefen, 2003; Gefen et al., 2003; Lee & Lee, 2009; Venkatesh & Davis, 2000). In other words, if perceived ease of use is the cost and perceived usefulness is the benefit of utilizing a technology (Davis, 1989), the less is the perceived cost, the higher is the perceived benefit.

Although originally TAM posits that the perceived ease of use influences both perceived usefulness and behavioral intention (Davis et al., 1989), with time empirical results created question marks about its direct impact on behavioral intention. A meta-analysis showed that whereas the relationship between perceived ease of use and perceived usefulness is solid, the one between perceived ease of use on behavioral outcome is not stable (Lee et al., 2003). Especially, a prolonged utilization of a technology can cause perceived ease of use to lose its significance on intention over time (Davis et al., 1989; Venkatesh & Davis, 2000; Venkatesh, et al., 2003). On the other hand, perceived usefulness showed off to be the key predictor in empirical investigations both at technology utilization in general and at online shopping in particular (Benbasat

& Wang, 2005; Davis, 1989; Gefen et al., 2003; Koufaris, 2002; Lee et al., 2003; Lee & Lee, 2009; Venkatesh & Davis, 2000; Venkatesh et al., 2003).

In comparison among the two equally useful systems the easier one shall be preferred; however if a system shows itself off critical performance, it is to be accepted in spite of the difficulty to use, or in contrary a very simple application shall not be accepted, if not useful (Davis, 1989). Accordingly, within the study only perceived usefulness of the recommendation is used to predict intention to adopt. It is proposed that the more useful, i.e. accurate and novel a recommendation is the higher will be intention to adopt.

CHAPTER 4

RESEARCH METHODOLOGY

The study uses a mixed methodology, i.e. an experiment and a survey. First the experiment divides the participants into different conditions by the designed manipulations and interrogates the simple adoption feedback to the recommendation provided. Then the same groups continue the study by answering the survey questions, which aim to understand the behind the scene dynamics of the first hand delivered adoption feedback. At this step, trust provided to the recommendation source is compared together with perceived ease of use and perceived usefulness of the recommendation received. Accordingly, these parts of the study utilize group comparison tools. At the following step, the structure built with these constructs leading to intention to adopt is studied in detail, thanks to a SEM analysis.

When a participant has accepted to take part at the study, she is first delivered with the experimental stimulus and then she receives the questionnaire. The whole process uses one single data collection instrument; the next sections detail the design of this instrument and the flow of the process.

4.1 Design

In selecting the product and industry, forming up the manipulations, naming AI and Human advisor, and designing the flow of the experiment, several examples within the literature are studied, as summarized at Table 1.

Table 1. Literature Summary Comparing AI and Human Advisors

Article	Product type	Recommendation Source	Preferred Source
Dijkstra, 1999	Law advice	An expert system	AI
Senecal and Nantel, 2004	Calculator/Wine	Recommender system / Other consumers / Team of experts	AI
Kennedy et al., 2018	Criminal judging	An algorithmic aggregation of others/ An algorithm/A random other participant/ The average of other participants/ A judge with experience	AI
Logg et al., 2019	Weight/Song rank/ Personal attraction/ Rank of airline passengers	An algorithm/A statistical model/ Self/Past participant(s)/ Average of others/ Aggregation of others/Others	AI
Promberger and Baron, 2006	Medical operations	A computer program/Your physician	Human advisor
Önkal et al., 2009	Stock prices	Statistical model/Financial expert	Human advisor
Dietvorst et al., 2015	MBA applicants success/ Airport rank by passenger number	A statistical model/Self/ A past participant/Human judge	Human advisor
Castelo et al., 2019	A list of activities differing in level of subjectivity	An algorithm/Our expert algorithm/ A well qualified person/Our experts	Human advisor
Longoni et al., 2019	Stress level/ Dermatological cancer/ Having a surgery	Computer/Automated provider/ Robotic/Doctor or Physician/ Human	Human advisor
Luo et al., 2019	Financial service	AI voice chatbot/Service agent	Human advisor
Mende et al., 2019	Medical/ Educational/Food	Humanoid service robot/Human	Human advisor
Yeoman, et al., 2019	Jokes	Computer algorithm / Recommender system/Another user	Human advisor
Wang et al., 2015	Digital camera/ Printer	Collaborative filtering/Content filtering	Content filtering
Gai and Klesse, 2019	News articles/ Paintings/Novels	User based/Item based recommendation	User based

The experimental part of the study, questioning the choice between AI and Human advisors, is designed according to the samples at the algorithm adoption literature. The research is set up with the description of a vignette, where the participants consider themselves in an online shopping environment with a specific purpose. Asking the participant to imagine herself in a described hypothetical environment to provide related feedback is used at several studies (e.g. Cyr et al., 2009; Gai & Klesse, 2019; Kennedy et al., 2018; Leung, Paolacci, & Puntoni, 2018; Longoni et al., 2019; Promberger & Baron, 2006; Whitley, Trudel, & Kurt, 2018; Zhang, 2020; Zhu, Wang, & Chang, 2018).

Then the experimental part is followed by a questionnaire in order to collect detailed data to understand the reasons behind the choice stated at the experiment.

4.1.1 Industry and product

The industry for the experiment is fashion. Online shopping and recommendation using are accustomed for fashion items. Hence, the participants of the study shall have experience in such a shopping process and shall not have any difficulty to imagine the experimental set-up.

In addition, selecting fashion as the subject of the study is in line with the developments in online shopping. The recommendation effectiveness literature has mainly focused on products like camera, laptop, mouse, printer etc., which are easy to differentiate by objective features (e.g. Kim et al., 2010; Wang et al., 2015; Wang et al., 2016; Zhang & Curley, 2018). Nevertheless, an evolution can be observed at online consumer behavior. At the first steps of online shopping, for example in 1998 the highest ranking items were the ones which are standard in quality description (Cai & Xu, 2007). However as of today, the concern of a missing subjective evaluation at online shopping has diminished, accordingly apparel and footwear are among the prominent items in online shopping expenditures (ETBIS, 2021; Kemp, 2021a).

Specific within the fashion industry, the product for the experiment is chosen as sneakers. Clothing, including footwear as well as apparel and accessories, has the highest percentage of shoppers (Eurostat, 2021). When considered separately, the leader category is clothing, as 57% of online shoppers reported to have bought a clothing item within a year, which is closely followed by footwear with 47% (Statista, 2018). In specific, sneakers are one of the most sold items within online shopping in Turkey (Twentify, 2018). As sneakers appeal to both genders, to all income levels, and to any age group, they are a very common and achievable product for any consumer. Hence, this choice contributed to the flexibility in participant selection.

4.1.2 Preparation of visuals

A pool of sneaker visuals has been created for the experiment. The visuals are taken from a retailer site as in the study of Whang and Im (2018). One single site is used as a source in order to provide unity in terms of visual size, visual background, and positioning of the product.

The first criterion of a visual to be added to the pool is considered as unfamiliarity with the brand. Decreasing or eliminating any brand related prior attitude is important (Ghasemaghaei, 2020); therefore, existence of a logo and any sign of the brand are avoided. In addition, the source site is selected to be international and offering luxurious options. An up-to-down price filtering is realized and the visuals of the highest priced items are included to the pool in order to avoid a visual recognition of a specific brand/model.

The second criterion is taken as assuring gender neutrality. Sneakers are advantageous as they appeal to both women and men (Ghasemaghaei, 2020). For this purpose, a female and a male judge discussed the visuals whether being gender neutral or not. Accordingly, only the sneaker visuals, at which both the female and male judges get at worst indecisive of gender neutrality, are used at the study.

The selected sneaker visuals are then tested at a pilot study realized with 16 participants based on a convenience sample. The participants did not state a familiarity with the offered alternatives and did not experience an irritation due to gender neutrality. If any one of the models has been considered as not appealing, this did not affect the whole assortment or the site evaluation.

However, at the pilot test some participants challenged the assortment as not including any provocative design option; hence, while sticking to the above process, some models are replaced with the ones having different colors and heel/toe structures.

4.1.3 Manipulations

The experimental study includes two manipulations: recommendation source and recommendation type. The rest of the study, i.e. vignette description, industry and product, experimental flow and the questions measuring the model variables, is exactly same for all groups.

The first manipulation, recommendation source, is differentiated as either being AI or Human. The second manipulation, recommendation type is discriminated as being Basic, Upsell, Cross sell and Design. Hence the experiments are 2 (recommendation source: AI - Human) x 4 (recommendation type: basic - upsell - cross sell - design) between subjects as presented at Table 2.

Table 2. Manipulation Design of the Study

		Recommendation Type			
		Basic	Upsell	Cross sell	Design
Recommendation Source	AI				
	Human				

In terms of recommendation source, it is important to decide how to name AI and Human advisors. To name AI advisor, several terms from the literature are considered such as recommendation, algorithm, computer, program, software, system, statistical model, database etc. (e.g. Castelo et al., 2019; Dietvorst et al., 2015; Logg et al., 2019; Longoni et al., 2019; Promberger & Baron, 2006; Senecal & Nantel, 2004; Yeomans et. al, 2019).

A practical answer is received from a research realized in 2021. A research company investigated a very similar subject and interrogated the question of what comes to mind by hearing the word artificial intelligence (Demiralp, 2021). The first three terms coming into the minds were smart robots, technology/science, and computers, followed by concepts like software, programming, algorithm, and smart systems. Some participants showed a deeper knowledge in the subject and stated machine learning, machine intelligence, robotic coding, and even Turing test, where others gave examples of AI systems like Siri, Alexa, Google Assistant, Tesla, chatbots, navigation systems, or drones. Accordingly, it is decided that the term Artificial Intelligence would be understandable and appealing for the participants. It would be a direct naming of AI and cover a wider scope compared to algorithm, analysis, recommendations, or computer.

On the other hand, terminology for the Human advisor can include terms considering a profession like doctor (e.g. Longoni et al., 2019) and judge (e.g. Kennedy et al., 2018) or ordinary people as another person and the person herself (e.g. Dietvorst et al., 2015). Within the study, as a specific domain is chosen, it is decided to follow the professional advisor mentality. Therefore, the human recommendation source is called as Team of Designers. A hint like experts is specifically avoided in order to prevent a favor for the Human advisor, because such a commentary add on could transmit the ability, know-how and background of the advisor and work like an endorsement for the recommendation (Önkal et al., 2009).

Manipulation check for the recommendation source is realized by measuring the social presence. The perception created by the medium as if there are others actually present and as if an emotional human socialization is established refers to social presence (Fulk et al., 1987; Gefen & Straub, 2004; Kumar & Benbasat, 2006).

In terms of the recommendation type, the manipulation differs where the recommendation can emerge in four alternatives: Basic, Upsell, Cross sell and Design. Any basic product recommendation proposes alternatives from a vast offer to ease the search and decision making process for the consumer (Helmers et al., 2019). An upsell covers a higher priced item (Bose & Chen, 2009); whereas a cross sell recommendation changes the target product (Helmers et al., 2019). These three stages are actually used at the online shopping sites with a decreasing frequency from the basic recommendation to the upsell and cross sell ones. However, the fourth phase, where the consumer is asked to imagine the design capability of AI at an online shopping site, is very rare.

With this manipulation, the aim of the study is to test whether the reactions to different type of recommendations are similar for AI and Human advisors, in other words whether the mentality provided at the Uncanny Valley theory is applicable at a virtual form of AI (Mori et al., 2012). Any breaking point at otherwise linear feedback shall provide insights for the AI-Human comparison.

An attention check is realized for recommendation type manipulation by asking the participant to select the actually received recommendation among the four different recommendation types used at the study.

4.1.4 Process of experiment

Step 1 - Vignette description: After agreeing to participate at the study, the participant is provided with a vignette. She is asked to imagine herself surfing at an online shopping site, which has not been used before and met for the first time. The aim of the surf shall be buying a pair of sneakers for the coming season. The presented information states that the site has an assortment of various sneaker models, and that these models will be listed by a mixed order.

Within this description, consideration of buying is deliberately stated to increase the involvement into the experiment (Whang & Im, 2018). Also the site is described as being hypothetical so that any positive or negative prior thoughts specific for an e-vendor are omitted and any knowledge-based trust is prevented (Benbasat & Wang, 2005; Whang & Im, 2018). The contact with the site is declared as being for the first time in order to underline that the recommendation is based on the actual experience and to avoid any belief that there could be an impact of past behavioral steps. In addition, the presentation of the models is defined as in a mixed order, to block out the thoughts regarding price based or popularity based listing.

Step 2 - Model presentation: Then the participant starts to see visuals of sneaker models with the possibility to scroll up and down and enlarge the picture like in a real shopping site. The difference from a real website is that the visuals are not accompanied with any text regarding the brand, price, or features.

The presented assortment size includes 10 models before the recommendation. Within the literature, the assortment size shows different numbers. Studies aiming to manipulate choice complexity by increasing cognitive overload used up to 200 options (Maheswarappa, Sivakumaran, & Kumar, 2017). However, studies focusing on other aspects of the experience remained between four to nine alternatives offered (Fitzsimons & Lehmann, 2004; Gai & Klesse, 2019; Ghasemaghaei, 2020; Senecal & Nantel, 2004; Whang & Im, 2018; Yeomans et al., 2019; Zhu et al., 2018). Schrah, Dalal, and Sniezek (2006) compared different assortment sizes and showed that in terms of complexity an assortment of nine alternatives shall be accepted as medium, where 13 is high and five is low. Poursabzi-Sangdeh, Goldstein, Hofman, Wortman Vaughan, and Wallach (2021) used an assortment of eight alternatives in a short version of their experiment and 12 in a long version.

Within this stage, where the participant can surf between the model visuals, she is not let to state a like or a choice. First reason is not to let her leaving the assortment evaluation mentality and proceeding, as a phase difference could compound feedback for substituting and complementing product recommendations (Zhang & Bockstedt, 2020). Whereas recommendations for the substitutes are more effective at first stages, recommendations for the complements are more effective at the later ones (Zhang & Bockstedt, 2020; Zhu et al., 2018).

The second reason is that the intervening recommendation after a selection or a show of a like could cause a psychological reactance, a different construct out of this study's scope (Fitzsimons & Lehmann, 2004).

Lastly, at the later phases of a shopping process, personalization becomes more salient (Kumar et al., 2020) and personalization is specifically avoided within this study. Personalization has a very strong impact in online shopping (Berendt, Günther, & Spiekermann, 2005; Longoni et al., 2019; Whang & Im, 2018; Xiao & Benbasat, 2018). It causes customers to shop more (Xiao & Benbasat, 2018); leads consumers to be happy with the result and with the process, make less search, and perceive less effort (Xiao & Benbasat, 2018); and get ready to openly share a lot of data (Berendt et al., 2005). Within the boundaries of the experiment setup, i.e. having a hypothetical frame and a vignette, it is difficult to transfer the perception of a personalized offer, especially for the Human advisor. Hence, the potential impact of personalization is avoided.

Step 3 - Recommendation source manipulation: While surfing, after the demonstration of ten alternatives, the next click, supposedly for the next page of models, takes the participant to a pop up message regarding a recommendation. This pop up message includes the manipulation of recommendation source as being AI or Human. The treatment is randomized automatically as within the studies using online panel data or working with Amazon MTurk (e.g. Ghasemaghaei, 2020; Martin, Borah, & Palmatier, 2017; Xiao & Benbasat, 2018; Yin, Wortman, Vaughan, & Wallach, 2019).

The pop up message provides the same explanation for both sources and stresses that the recommendation source is collecting worldwide information about the sneaker fashion and is following the trends. This explanation is kept short and general as a more detailed explanation of the recommendation can affect trust in AI (Rai, 2020; Wang & Benbasat, 2008).

Step 4 - Recommendation type manipulation: After the pop up message, the next click leads the participant to the visual of the recommended product, where the recommendation type is manipulated. The recommended product visual is presented with the repetition of the recommendation source.

For the recommended product, the same sneaker visual is used for basic, upsell, and design conditions. For the cross sell condition, a backpack, again a gender-neutral choice is presented.

The group at the basic condition receives the recommendation as a different sneaker model. The group at the upsell condition gets the offer as an option produced with environmentally conscious material but is slightly higher in price. The third group being at the cross sell condition is provided with a backpack to accompany the sneakers. The last group at the design condition receives the recommendation as a model drawn and designed by the recommendation source.

Step 5 - Questionnaire: Having seen the recommendation, the participant receives the questionnaire, starting with the intention to adopt the recommendation questions and continuing with the other variables of the study.

The experiment flow is tested with 16 participants based on a convenience sample. Each condition had two testers and hence in addition to testing the overall process, it was possible to check whether there is an issue specific for any one condition. No particular issue has been observed.

4.2 Data collection

Data is collected online by cooperating with a market research company. Compared to a convenience sampling, the utilization of online panel members provided a more balanced sample distribution in terms of demographic characteristics. In particular, TAM studies are criticized by utilizing student samples (Lee et al., 2003), therefore working with online panel members eliminates this limitation as well.

The market research company managed randomized treatment of the experiment and collected the answers for the questionnaires. Additionally, the firm made it possible to act fast and hence prevent any potential concerns regarding a lengthened timeframe at the experimental study. The run out of the study is completed within one week of time in July 2021 and raw data is received from the research company.

The sample consisted of 400 participants in total, i.e. 50 per each condition. The sample size is accepted as being adequate for AI-Human comparisons and model analysis. For group comparison analyzes like Analysis of Variance (ANOVA) and Multivariate Analysis of Variance (MANOVA), the participant number at each condition shall be higher than the number of the dependent variables and practically higher than 20 (Hair, William, Bary, & Anderson, 2010). On the other hand, to study the structural relations at SEM analysis, the sample sizes starting with hundred participants are acceptable (Hair et al., 2010).

4.3 Measures

The study used measures validated within the literature for all of the constructs. McKnight et al. (2002) worked out a basis for trust measurement specifically for online shopping. The scale they developed appealed to both mind and heart of the person with the trusting beliefs and trusting intentions, respectively. Wang et al. (2016) developed and adopted the trusting believes part specifically for recommendations and offered the scale as a measurement tool for cognitive trust. On the other hand, the trusting intentions part of McKnight et al. (2002) overlap with the emotional trust scale developed by

Komiak and Benbasat (2006) in relation to recommendations. This study used the cognitive trust scale of Wang et al. (2016) and the emotional trust scale of Komiak and Benbasat (2006).

In terms of TAM measurement, the literature mainly took the scales of Davis (1989) and Davis et al. (1989) and adopted them for different technologies like websites (e.g. Gefen, 2003; Koufaris, 2002), organizational IT systems (Venkatesh & Davis, 2000) or recommendation agents (Benbasat & Wang, 2005). For perceived usefulness and perceived ease of use constructs, the scales used by Koufaris (2002) and by Lee and Lee (2009) are adapted.

In perceived ease of use scale, two differentiations are realized. First, as the recommendation agent within this study is supposed to work without a deliberate act of the user, questions about learning are omitted; second, the question regarding the system being clear and understandable is divided into two in order to increase the understanding and appeal to the specific case of recommendations black box logic.

For the construct intention to adopt, the scale is taken from Benbasat and Wang (2005).

The resulting questionnaire is tested by a pilot study with 16 participants based on a convenience sample and provided no concerns.

CHAPTER 5

RESULTS

5.1 Profile of the sample

Profile of the raw data sample is presented at Table 3 and Table 4.

Table 3. Demographics of Raw Data Sample

		N	%
Gender	Female	199	49.8
	Male	201	50.3
Age	18-19	25	6.3
	20-24	60	15.0
	25-29	60	15.0
	30-34	63	15.8
	35-39	56	14.0
	40-44	51	12.8
	45-49	45	11.3
	50-54	40	10.0
Education	Elementary school graduate or high school student	3	0.8
	High school graduate	144	36.0
	University student	52	13.0
	University graduate	185	46.3
	Master/PhD student/graduate	16	4.0
Work Status	Student	51	12.8
	Working	239	59.8
	Unemployed/Retired/Housewife	110	27.5
Income	2,000TL or less	47	11.8
	2,001-4,000TL	106	26.5
	4,001-6,000TL	111	27.8
	6,001-8,000TL	73	18.3
	8,001-10,000TL	43	10.8
	10,001TL or more	20	5.0

Table 4. Online Shopping Habits of Raw Data Sample

		N	%
Online shopping view frequency (excluding supermarket shopping and food orders)	Everyday	161	40.3
	3-4 times a week	107	26.8
	1-2 times a week	44	11.0
	2-3 times a month	48	12.0
	1-2 times a month	28	7.0
	Once every two months	6	1.5
	Once every three months or less	6	1.5
Online shopping purchase frequency (excluding supermarket shopping and food orders)	Everyday	57	14.3
	3-4 times a week	81	20.3
	1-2 times a week	90	22.5
	2-3 times a month	108	27.0
	1-2 times a month	47	11.8
	Once every two months	12	3.0
	Once every three months or less	5	1.3
Online shopping experience (excluding supermarket shopping and food orders)	Less than a year	40	10.0
	1-2 years	59	14.8
	2-4 years	94	23.5
	4-6 years	89	22.3
	6-8 years	40	10.0
	8-9 years	28	7.0
	More than 9 years	50	12.5

Worldwide, women are slightly more active than men in online shopping (Kemp, 2021b). Specific for Turkey, men surpass women in online shopping (Kemp, 2021c), however at the same time online shopping of women in apparel sector is higher than men (Twentify, 2018). Hence, the study used a balanced gender distribution. In terms of age, the distribution of the total age groups in Turkey (Türkiye İstatistik Kurumu [TÜİK] Age, 2020) is echoed, as all age groups are active at online shopping for apparel (Twentify, 2018; Kemp, 2021c). The statistics for Europe showed as well that the percentage of internet users realizing online shopping is equal for 16-24 and 25-54 age groups (Eurostat, 2021). The sample is also in line with the general population statistics about working status (TÜİK Work, 2020).

However, concerning education level, there is a discrepancy between the sample and overall statistics for Turkey. In specific, the education level of the sample is higher than the general population education (TÜİK, Education, 2021). As the sample consists of people who actively opted to be a member of an online research panel, this difference is inevitable. Nevertheless, since the subject of the study refers to a high-level technology, this structure is considered to be in line with the targets of the research.

View frequency and purchasing frequency distributions are also different compared to the reports provided for apparel category in 2018 (Twentify, 2018). View is skewed to a higher frequency for everyday and 3-4 times a week, whereas purchase frequency is higher for all levels until 1-2 times a month option. However, this result is expected because Covid19 period realized a splendid impact in online shopping (TÜSİAD, Çok Kanallı Perakende Raporu, 2021) and the sample is structured by the members of an online panel, i.e. active in digital world.

5.2 Data structure

There are no missing values within the data. To analyze the engagement of the participants, the standard deviation of the responses to Likert scale questions is calculated. Accordingly, nine cases are eliminated at having a standard deviation of zero, i.e. having checked the exact same answer to all Likert scale measured questions.

Attention check for recommendation type has been realized by the research company. The participants, who cannot correctly answer what type of product offer they have received, could not finalize the study.

Manipulation check for recommendation source has been realized with the measurement of the experienced social presence. Social presence is related to the emotional feedback of having a human on the other side of the medium and is measured by perceptions of human contact, personalness, sociability, human warmth, and human sensitivity (Fulk et al., 1987; Gefen & Straub, 2004; Kumar & Benbasat, 2006). Online shopping is not based on an actual interactive human communication; however, the sites try to increase this feeling with several tools like welcoming the user by her name, adding comments of other users or some contact possibilities such as a chat option (Gefen & Straub, 2004; Kumar & Benbasat, 2006). Recommendations are factors influencing perceived social presence as well (Choi, Lee, & Kim, 2011; Kumar & Benbasat, 2006), hence some level of social presence could be observed at AI condition. However, the observed social presence when facing AI shall not be equal to a complete human contact perception.

The study used three social presence questions investigating perceived human contact, warmth, and sensitivity (Gefen & Straub, 2004). Accordingly, if a participant at AI condition has answered all these three questions with the maximum positive answer, she is accepted as failing the manipulation. In other words, she is not capable of grasping that there is not a human being on the other side. Having a sense of a definite human contact, without any slight doubt, makes the contrast between AI and a real human pointless, as both become the same. Accordingly, 44 cases from the AI condition are eliminated. Similarly, six cases are eliminated from the Human advisor condition as they answered to all three social presence questions as "*definitely not felt*."

The resulting data has 341 cases, which means that 14.75% of raw data is left out of the study. Such a ratio is in line with the literature. Meta-analyzes show elimination of

19.56% as an average for experimental studies (Abbey & Meloy, 2017), but report that at some cases figures can be as high as 34% (Cullen & Monds, 2020) or even 44.50% (Abbey & Meloy, 2017). For online data collection, the median rate of data loss is observed as 20.4% (Vecchio, Borrello, Cembalo, & Caso, 2020). In the literature streams, which this study is depending on, studies reported data elimination rates of 10% (Zhang & Bockstedt, 2020), 19% (Yeomans et. al, 2019), 22% (Choi et al., 2011), and 55% (Frederiks, Englis, Ehrenhard, & Groen, 2019).

Besides the concern of overall data elimination, another issue could be that AI has a bigger loss compared to Human advisor condition, hence creating an imbalance. However, such cases are also observed at the literature. For example, a study realized with online data collection method reported 15% and 60% of data loss at different experimental groups (Pedulla, 2014).

In any case, in order to check if this elimination causes a significant difference between the deleted and not deleted data, group comparison tests are realized. Tests verify that there is not a significant difference between the deleted and kept observations in terms of gender, age, education, working status, income, online shopping experience, and online shopping view frequency.

The only significant difference is observed in online shopping purchase frequency, where the deleted participants perform significantly less frequent online shopping compared to the kept ones. However, as the online shopping habits are measured with experience and view frequency as well, the difference at purchase frequency is neglected.

Accordingly, the hypotheses' testing is realized with the data cleaned of participants who are not engaged and who could not pass manipulation check.

The data shows normal distribution in terms of skewness and kurtosis for the indicators of the latent factors and demographic variables. Additionally, normality is ensured by the sample size being higher than 200 (Hair et al., 2010).

The structure of data used at further analysis is presented at Table 5 and Table 6.

Table 5. Demographics of the Study Sample

		N	%
Gender	Female	166	48.7
	Male	175	51.3
Age	18-19	22	6.5
	20-24	54	15.8
	25-29	45	13.2
	30-34	51	15.0
	35-39	49	14.4
	40-44	44	12.9
	45-49	38	11.1
	50-54	38	11.1
Education	Elementary school graduate or high school student	3	0.9
	High school graduate	118	34.6
	University student	47	13.8
	University graduate	162	47.5
	Master/PhD graduate/graduate	11	3.2
Work Status	Student	46	13.5
	Working	199	58.4
	Unemployed/Retired/Housewife	96	28.2
Income	2,000TL or less	40	11.7
	2,001-4,000TL	88	25.8
	4,001-6,000TL	103	30.2
	6,001-8,000TL	62	18.2
	8,001-10,000TL	34	10.0
	10,001TL or more	14	4.1

Table 6. Online Shopping Habits of the Study Sample

		N	%
Online shopping view frequency (excluding supermarket shopping and food orders)	Everyday	132	38.7
	3-4 times a week	91	26.7
	1-2 times a week	38	11.1
	2-3 times a month	45	13.2
	1-2 times a month	26	7.6
	Once every two months	6	1.8
	Once every three months or less	3	0.9
Online shopping purchase frequency (excluding supermarket shopping and food orders)	Everyday	38	11.1
	3-4 times a week	67	19.6
	1-2 times a week	79	23.2
	2-3 times a month	99	29.0
	1-2 times a month	44	12.9
	Once every two months	10	2.9
	Once every three months or less	4	1.2
Online shopping experience (excluding supermarket shopping and food orders)	Less than a year	30	8.8
	1-2 years	53	15.5
	2-4 years	81	23.8
	4-6 years	80	23.5
	6-8 years	33	9.7
	8-9 years	23	6.7
	More than 9 years	41	12.0

5.3 Scale validations

5.3.1 Exploratory factor analysis

Exploratory factor analysis (EFA) is realized in order to test the structure of the scales and to classify the variables under logical and interpretable factors (Sekaran, 2003).

The sample size of 341 is adequate for EFA, since it is over the minimum size of 50 observations, has more observations than variables, and surpasses the minimum ratio of 5:1 and even the conservative ratio of 10:1 between observations and variables (Hair et al., 2010). All variables within the data are metric, measured by Interval scale. All dependent and independent variables of the study are included to the same EFA.

The appropriateness of the data for the factor analysis is checked by the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy test and Bartlett test of sphericity. As a whole, the data proved to be appropriate for EFA according to the KMO measure of sampling adequacy (KMO = 0.972) and Bartlett's test of sphericity (Bartlett's test (276) = 11600.535, $p = 0.000$). KMO value, being higher than 0.800, shows a perfect fit of data for EFA and the Bartlett' test being statistically significant shows that the correlations between the variables are enough (Hair et al., 2010). In addition, at the Measure of Sampling Adequacy (MSA) analysis all variables have an MSA value above 0.50, so all are included to EFA (Hair et al., 2010).

The analysis also showed that all of the variables have communalities above 0.60, therefore both component and common factor analyzes are expected to provide similar results (Hair et al., 2010). Since the target of the analysis is to summarize and reduce data for further utilization in other analyzes, the component factor analysis method is utilized. All measurement scales are borrowed from the existing literature, therefore the number of the variables in the study is used as the number of factors. The expected factors have been three factors of cognitive trust (ability, integrity, benevolence), emotional trust, perceived usefulness, perceived ease of use, and intention to adopt. The analysis is realized with a Varimax rotation and 89.8% of the total variance is explained.

The rotated component matrix showed that five factors, cognitive trust ability, cognitive trust integrity, cognitive trust benevolence, emotional trust, and intention to adopt are structured without a problem. However, cross loadings are observed between perceived usefulness and perceived ease of use.

Hence, a second EFA is realized with only these two factors. Within this analysis as well, the data proved to be appropriate for EFA by KMO measure of sampling adequacy (KMO = 0.0.927) and Bartlett's test of sphericity (Bartlett's test (21) = 2965.547, p = 0.000). Similarly, the individual values of MSA analysis are above 0.50, and all of the variables have communalities above 0.60. According to the number of the variables kept for the second run, the factor number to be extracted is set as two. The analysis is realized with a Varimax rotation and 89.1% of the total variance is explained. The results showed that two items of perceived ease of use, namely PEoU2 and PEoU3, have a loading above 0.5 to perceived usefulness. Since their loadings to perceived ease of use are very powerful, they are kept for a check at the confirmatory factor analysis. However, one item of perceived usefulness (PU4) showed a similar level of loading to both perceived usefulness and perceived ease of use, therefore this item is deleted.

After deleting PU4, EFA is rerun with all variables. The results showed appropriateness of the data by KMO measure of sampling adequacy (KMO = 0.971) and Bartlett's test of sphericity (Bartlett's test (253) = 11030.780, p = 0.000). Again, the individual values of MSA analysis are above 0.50, and all of the variables have communalities above 0.60. The analysis is realized with a Varimax rotation; the total variance explained has slightly increased and reached to 90.1%. The rotated component matrix showed that cognitive trust ability, emotional trust, and intention to adopt are structured without a problem. However, perceived usefulness and perceived ease of use slightly overlap at PU3, and cognitive trust benevolence and cognitive trust integrity had a similar loading at CTBen3.

Therefore, a new run of EFA is realized with only these four variables, i.e. perceived usefulness, perceived ease of use, cognitive trust benevolence, and cognitive trust integrity. The data proved to be appropriate for EFA by the KMO measure of sampling adequacy (KMO = 0.951) and Bartlett's test of sphericity (Bartlett's test (78) = 5691.827, p = 0.000). The individual values of MSA analysis are above 0.50, and all of the variables have communalities above 0.60. The analysis is realized with a Varimax rotation and 89.4% of the total variance is explained. The results showed that although the concern in regard of PU3 has been solved, the one regarding to CTBen3 continues.

A last EFA has been realized with keeping only cognitive trust benevolence and cognitive trust integrity. The data proved to be appropriate for EFA by the KMO measure of sampling adequacy (KMO = 0.923) and Bartlett's test of sphericity (Bartlett's test (21) = 2753.972, p = 0.000). The individual values of MSA analysis are above 0.50, and all of the variables have communalities above 0.60. The analysis is realized with a Varimax rotation and 88.1% of the total variance is explained. The results showed that CTBen3 still has a loading higher than 0.5 to both cognitive trust benevolence and cognitive trust integrity, however the difference within the cross loading results are high. Hence, the received structure is accepted as valid and further testing is left to Confirmatory Factor Analysis (CFA) study.

For the achieved structure, the Cronbach alpha reliabilities are checked whether an exclusion of any item would cause a higher reliability result; the results showed that there is not such a case at any factor. The achieved factor structure, where all variables are included to the same EFA, and the related Cronbach alpha reliabilities are presented in Table 7.

Table 7. Factor Structure

Factor	Items	Factor Loadings	Variance Explained (%)	Reliability
Cognitive Trust Ability	CTAb1	.643	13.681	.956
	CTAb2	.656		
	CTAb3	.713		
	CTAb4	.602		
Cognitive Trust Integrity	CTIn1	.710	16.393	.951
	CTIn2	.697		
	CTIn3	.653		
	CTIn4	.664		
Cognitive Trust Benevolence	CTBen1	.576	7.717	.936
	CTBen2	.586		
	CTBen3	.531		
Emotional Trust	ET1	.690	13.898	.957
	ET2	.719		
	ET3	.706		
Perceived Usefulness	PU1	.609	8.314	.939
	PU2	.603		
	PU3	.551		
Perceived Ease of Use	PEoU1	.801	16.155	.951
	PEoU2	.720		
	PEoU3	.749		
Intention to Adopt	INT1	.761	13.986	.954
	INT2	.747		
	INT3	.703		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy				.971
Bartlett's Test of Sphericity		Chi-Square		11030.78
		df		253
		Sig.		.000

5.3.2 Confirmatory factor analysis

In order to confirm the structure of the constructs and show how good they are indicated by the measured variables, a CFA has been run (Hair et al., 2010). The sample size of 341 is adequate for the CFA for an overall fit analysis using whole data. It is also adequate for further multisample analyzes after dividing data into two groups according to recommendation source. In these studies, AI condition has 153 and Human advisor condition has 188 observations. The minimum threshold is stated as 150 when there are seven or less constructs, when communalities are above .5, and when there is not any issue of identification (Hair et al., 2010).

Like within the exploratory factor analysis, all of the dependent and independent variables of the study are included to the same CFA. The results showed that the Chi-square (χ^2) is 501.126 with 209 degrees of freedom and p = .000. A significant χ^2 shows that the estimated and observed covariance matrices do not match. However, considering the sample size, further fit statistics can be considered (Hair et al., 2010).

Rule of thumb states that at least one absolute and one incremental fit index shall be audited (Hair et al., 2010). In terms of absolute fit indices, first Root Mean Squared Error of Approximation (RMSEA) is checked. RMSEA for the model is .064, i.e. below 0.080, which is a threshold for a model with twenty-three variables measured by a sample of 341 (Hair et al., 2010). The Standardized Root Mean Square Residual (SRMR) is .018, below the conservative guideline of .050 (Hair et al., 2010). On the other hand, the normed χ^2, calculated as the division of the χ^2 by the degrees of freedom, is 2.4 and remains within the accepted limits of 2.0 and 5.0 (Hair et al., 2010).

In terms of incremental fit indices, Comparative Fit Index (CFI), the mostly used index, is .974, i.e. above the threshold of .900 (Hair et al., 2010). Similarly, the incremental fit indices Normed Fit Index (NFI) and Relative Fit Index (RFI) are above the cut off level as well. The fit indices are summarized in Table 8 and the overall model is presented at Figure 6.

Table 8. Confirmatory Factor Analysis Fit Indices for Overall Data

Chi-square (χ^2)	
Chi-square	= 501.126
Degrees of freedom	= 209
Probability level	= .000
Absolute Fit Indices	
RMSEA	= .064
SRMR	= .018
Normed χ^2	= 2.398
Incremental Fit Indices	
CFI	= .974
NFI	= .956
RFI	= .946

There is a high convergent validity as all standardized loadings are significant and have a value above I .700 I, which is stated as ideal by Hair et al. (2010). To check the discriminant validity, the Average Variance Extracted (AVE) of each factor is compared against the squared correlation of this factor with other factors. This threshold is met since all AVE estimates are higher than the squared correlation with other factors and hence discriminant validity is ensured (Fornell & Larcker, 1981; Hair et al., 2010).

As further studies will involve the comparison of two groups, i.e. AI and Human advisors, the measurement model is also checked for configural, metric, and scalar invariance of multisamples.

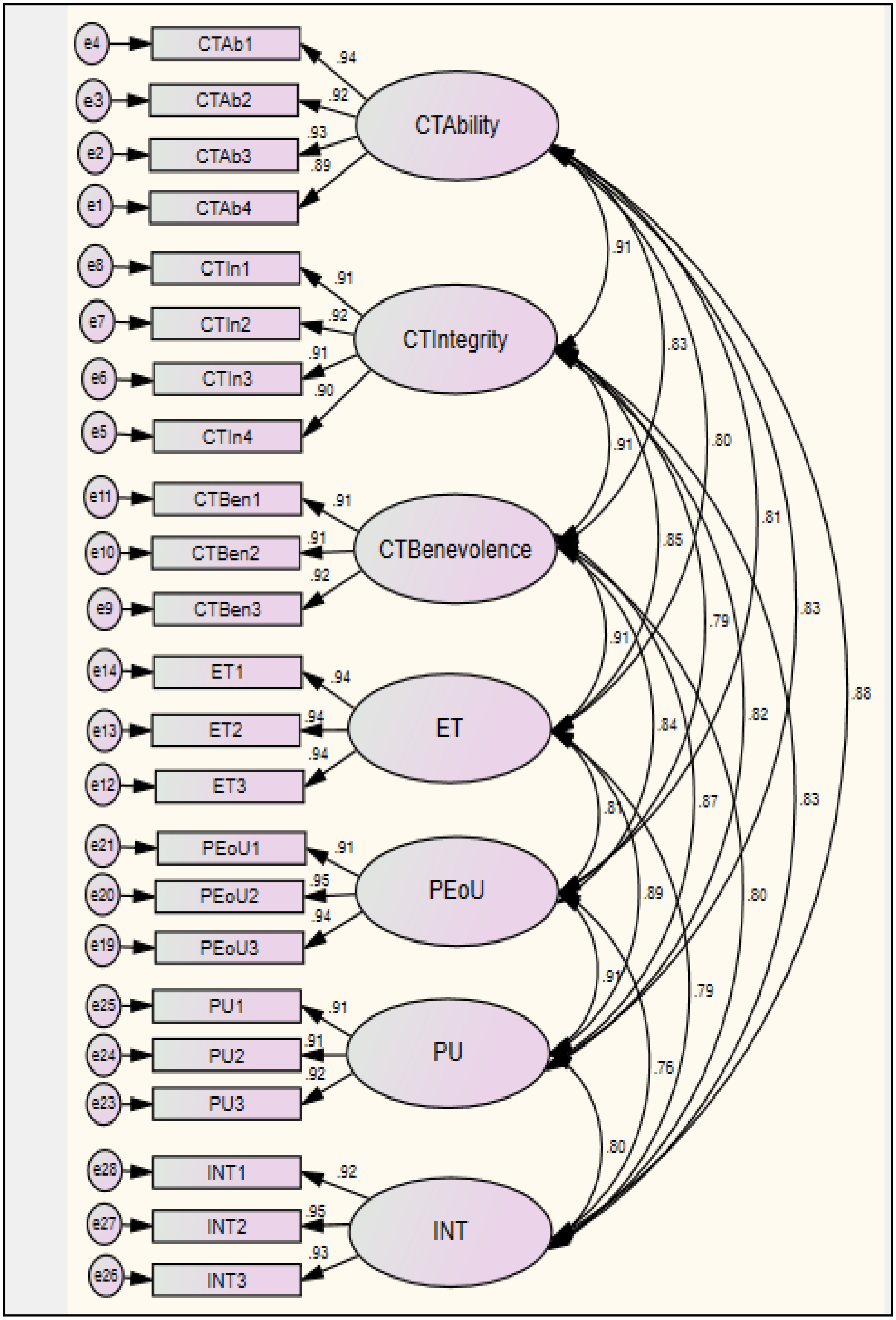


Figure 6. Confirmatory factor analysis

The first step is the configural invariance test. The configural invariance states that the measurement model structure is the same for all groups concerned (Hair et al., 2010). To realize configural invariance test, data of the study is divided into two, as AI and Human advisor conditions. Then the measurement model is rerun simultaneously for these two groups without any constraints (Hair et al., 2010). The results showed that Chi-square (χ^2) is 954.923 with 418 degrees of freedom and a *p* value of .000. The absolute fit indices show a good fit of the model with RMSEA = .062, SRMR = .028, and the normed χ^2 = 2.3. Similarly the incremental fit indices support the model fit with CFI = .952, NFI = .918 and RFI = .901. Hence, configural invariance is assured. Fit indices are summarized in Table 9.

Table 9. Fit Indices after Data Division into AI and Human Advisor Groups

Chi-square (χ^2)	
Chi-square	= 954.923
Degrees of freedom	= 418
Probability level	= .000
Absolute Fit Indices	
RMSEA	= .062
SRMR	= .028
Normed χ^2	= 2.284
Incremental Fit Indices	
CFI	= .952
NFI	= .918
RFI	= .901

The metric invariance is checked at the next step. Metric invariance questions utilization of the measurement variables, i.e. how they are understood across the two different groups, hence if the metric invariance is ensured, the group differences can be analyzed through a straightforward comparison (Hair et al., 2010). For this purpose, the data is kept as two groups like at the configural invariance test. However, this time all regression weights between factors and observed variables are constrained. The Chi-square (χ^2) difference between the alternative models, with and without constraints is insignificant, indicating that the two models are invariant. Metric invariance is ensured as presented at Table 10.

Table 10. Metric Invariance of AI and Human Advisor Groups

	Chi-square	*df*	*p*
Unconstrained Model	954.923	418	
Fully Constrained Model	973.484	441	
Number of groups		2	
Difference	18.561	23	.726

The scalar invariance is a further step in investigating the invariance between the groups at the study. If scalar invariance is ensured, the means of the variables can be compared across the different groups (Hair et al., 2010). Still keeping the data as separated into two, AI and Human advisors, this time measurements and intercepts are constrained. The model comparison between an unconstrained and constrained model is significant (p = .022), hence we could not state a full scalar invariance.

In following, a partial scalar invariance is investigated. When at least two items per factor are kept equal, i.e. invariant, and others are released free, a partial scalar invariance can be achieved (Hair et al., 2010). Accordingly, the intercept of two items, where the estimates had the highest difference between AI and Human advisors, have been unconstrained. After releasing these two items, i.e. CTIn4 and ET3, the model comparison get insignificant (p = .051) indicating a partial scalar invariance.

5.4 Hypotheses testing

5.4.1 Study 1: AI vs. Human - advisor differentiation in adopting the advice

H1: Human advice will be preferred over AI advice

H2: The preference of Human advice over AI advice shall differ according to the recommendation type

The choice between AI and Human advisors is investigated through a 2x4 full factorial ANOVA. The group sizes are higher than the practical threshold of 20 per condition and there is not a big difference in between the groups (Hair et al., 2010). The distribution of participants to the conditions is presented at Table 11 and detailed descriptive statistics are presented at Table 12.

Table 11. Sample Distribution in Manipulated Conditions

		Recommendation Type				
		Basic	Upsell	Cross Sell	Design	
		N	*N*	*N*	*N*	Total
Recommendation Source	AI	43	39	32	39	153
	Human	49	49	43	47	188
	Total	92	88	75	86	341

Table 12. Descriptive Statistics in Manipulated Conditions

Recommendation Type	Recommendation Source	Mean	Std. Deviation	*N*
Basic	AI	5.318	1.577	43
	Human	6.075	1.237	49
	Total	5.721	1.449	92
Upsell	AI	4.735	1.415	39
	Human	5.408	1.539	49
	Total	5.110	1.514	88
Cross Sell	AI	5.365	1.578	32
	Human	5.814	1.413	43
	Total	5.622	1.492	75
Design	AI	5.419	1.304	39
	Human	5.787	1.501	47
	Total	5.620	1.419	86
Total	AI	5.205	1.482	153
	Human	5.770	1.436	188

The analysis has intention to adopt as the dependent variable and recommendation source and recommendation type as the fixed factors. Equality of variance is ensured by a nonsignificant Levene's test as presented at Table 13.

Table 13. Equality of Error Variances - Study 1

F	*df1*	*df2*	Sig.
.650	7	333	.715

The results showed that there are significant main effects of both recommendation source (*F* = 12.635, *p* = .000) and recommendation type (*F* = 3.332, *p* = .020). However, no significant interaction effect is observed as presented at Table 14.

Table 14. Main Effect and Interaction Effect - Study 1

	F	Sig.
Recommendation Source	12.635	.000
Recommendation Type	3.332	.020
Recommendation Source * RecommendationType	.345	.793

Intention to adopt is higher when the advise is received from a Human advisor (*M* = 5.77) compared to AI (*M* = 5.21) as demonstrated at Table 12. Hence, H1 is supported; a Human advisor is preferred over an AI advisor.

However, H2 is not supported, i.e. the preference of a Human advisor over AI does not show a difference according to the type of the recommendation. The preference of a Human advisor is observed at all recommendation types as presented at Figure 7. Accordingly, as the difference is observed for both AI and Human advisors, the post hoc result of recommendation type main effect indicating a significant difference between basic and upsell recommendation types is neglected. The comparison of AI and Human advisors at each recommendation type and the related mean differences are presented at Table 15 and Figure 8.

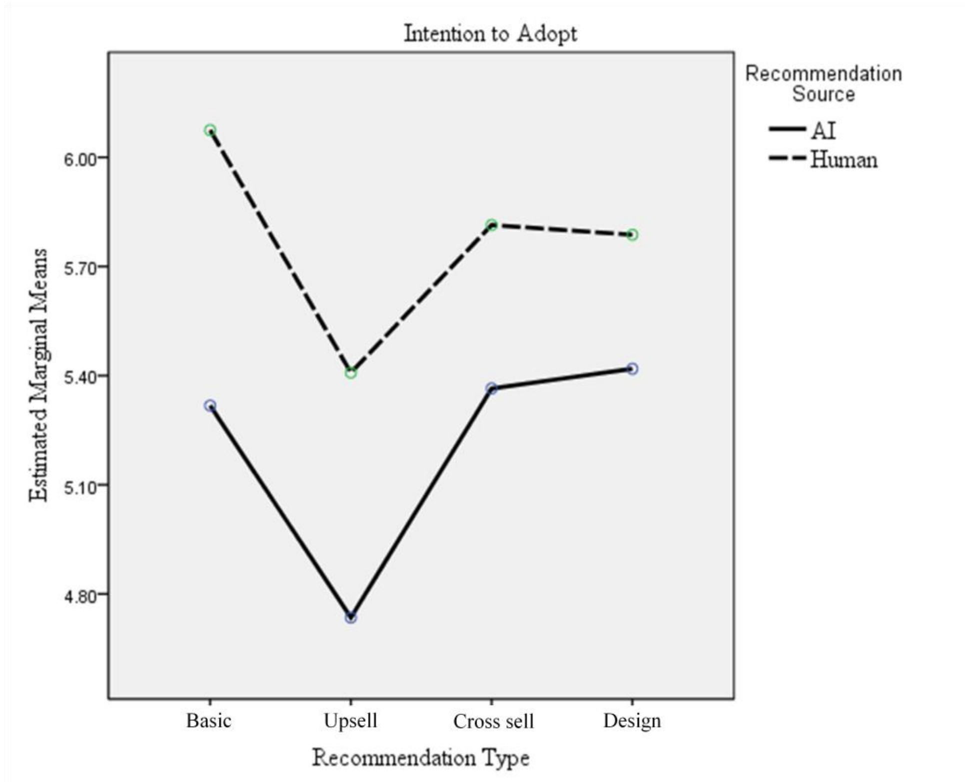


Figure 7. Comparison of recommendation source by recommendation type

Table 15. Mean Differences of Recommendation Types - Study 1

Recommendation Type	Recommendation Source	Intention To Adopt Mean	Mean Difference
Basic	AI	5.318	.757
	Human	6.075	
Upsell	AI	4.735	.673
	Human	5.408	
Cross sell	AI	5.365	.449
	Human	5.814	
Design	AI	5.419	.368
	Human	5.787	

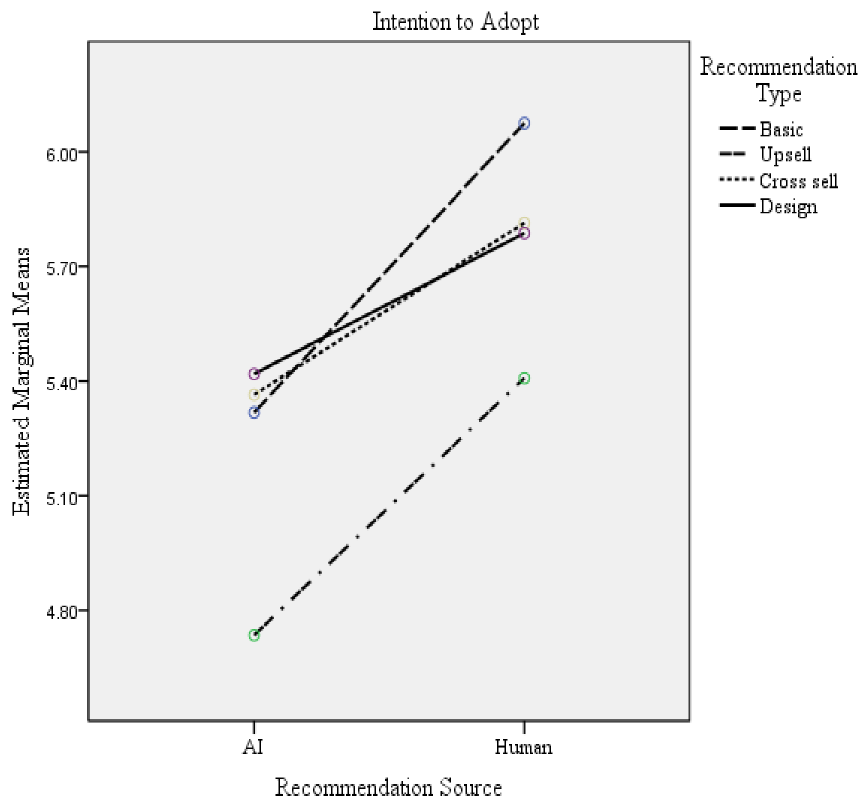


Figure 8. Comparison of recommendation type by recommendation source

Lastly, covariates are checked. Need for uniqueness and trust propensity are demonstrated in the literature as having an impact on algorithm aversion (Longoni et al., 2019; Wang & Benbasat, 2007). Adding them to the analysis as covariates again delivered a significant main effect of recommendation source and an insignificant interaction effect of recommendation source and recommendation type. The preference of a Human advisor over AI still holds at all types of recommendations.

5.4.2 Study 2: AI vs. Human - advisor differentiation in revealing cognitive and emotional trust

H3a: Human advisor is credited with higher cognitive trust compared to AI

H3b: The difference in cognitive trust credited to AI and Human advisors shall be influenced by the recommendation type

H4a: Human advisor is credited with higher emotional trust compared to AI

H4b: The difference in emotional trust credited to AI and Human shall be influenced by the recommendation type

At the next step, to investigate emotional trust and cognitive trust revealed at different recommendation source and recommendation type conditions, a MANOVA analysis is realized. Recommendation source and recommendation type are kept as the fixed factors, whereas emotional trust and cognitive trust get to be the dependent variables.

The data is appropriate for a MANOVA analysis with the cell numbers being higher than the number of dependent variables, similar across the conditions, and higher than the practical suggestion of 20 per condition (Hair et al., 2010). As MANOVA is specifically sensitive to outliers, the Cook' distance is checked for all dependent variables and all remain below the threshold of 0.5 (Pennstate, 2018).

At the next step, normality is checked both visually and statistically. Although normality could not be assured by statistical analysis neither by Kolmogorov - Smirnov nor by Shapiro-Wilk criteria, the visual check by $Q = Q$ plots showed no highly problematic issues for either one of the variables.

In addition, as the sample size is high, data is considered as normal. The variables are significantly correlated as presented at Table 16 and Table 17.

Table 16. KMO and Bartlett's Test - Study 2

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.833
Bartlett's Test of Sphericity	Approx. Chi-Square	1440.349
	df	6
	Sig.	.000

Table 17. Correlations - Study 2

		ET	CT Ability	CT Integrity	CT Benevolence
Emotional Trust	Pearson Correlation	1	.768	.814	.863
	Sig. (2-tailed)		.000	.000	.000
Cognitive Trust Ability	Pearson Correlation	.768	1	.874	.792
	Sig. (2-tailed)	.000		.000	.000
Cognitive Trust Integrity	Pearson Correlation	.814	.874	1	.856
	Sig. (2-tailed)	.000	.000		.000
Cognitive Trust Benevolence	Pearson Correlation	.863	.792	.856	1
	Sig. (2-tailed)	.000	.000	.000	

Unfortunately, the assumption of homoscedasticity between the groups could not be ensured. Although at the univariate level, Levene's test provided nonsignificant results showing that there is homogeneity between AI and Human advisor conditions, the Box's M test is significant, indicating a non-existence of homoscedasticity on the variables collectively as presented at Table 18 and Table 19 (Hair et al., 2010).

Table 18. Equality of Error Variances - Study 2

	F	*df1*	*df2*	Sig.
Emotional Trust	1.226	7	333	.287
Cognitive Trust Ability	1.202	7	333	.301
Cognitive Trust Integrity	.894	7	333	.511
Cognitive Trust Benevolence	1.061	7	333	.389

Table 19. Equality of Covariance Matrices - Study 2

Box's M	161.187
F	2.211
df1	70
df2	134369.370
Sig.	.000

Hence, the MANOVA study could not be realized further. As a remedy, recommendation source and recommendation type are taken separately as a single fixed factor and each one's impact on emotional trust and cognitive trust factors is analyzed by ANOVA.

For the analysis taking recommendation source as the single fixed factor, equality of variance is ensured by a nonsignificant Levene's test, presented at Table 20.

Table 20. Homogeneity of Variances- Study 2

	Levene Statistic	*df1*	*df2*	Sig.
Emotional Trust	1.727	1	339	.190
Cognitive Trust Ability	.097	1	339	.755
Cognitive Trust Integrity	.193	1	339	.661
Cognitive Trust Benevolence	1.634	1	339	.202

ANOVA results, presented at Table 21, show that there is a significant difference between AI and Human advisors. The impact of recommendation source is significant for emotional trust (F = 30.273, p = .000), for cognitive trust ability (F = 15.467, p = .000), for cognitive trust integrity (F = 16.212, p = .000), and for cognitive trust benevolence (F = 17.410, p = .000).

Table 21. ANOVA - Study 2

		Sum of Squares	*df*	Mean Square	*F*	Sig.
Emotional Trust	Between Groups	57.393	1	57.393	30.273	.000
	Within Groups	642.685	339	1.896		
	Total	700.078	340			
Cognitive Trust Ability	Between Groups	28.367	1	28.367	15.467	.000
	Within Groups	621.759	339	1.834		
	Total	650.126	340			
Cognitive Trust Integrity	Between Groups	31.858	1	31.858	16.212	.000
	Within Groups	666.175	339	1.965		
	Total	698.032	340			
Cognitive Trust Benevolence	Between Groups	36.573	1	36.573	17.410	.000
	Within Groups	712.111	339	2.101		
	Total	748.684	340			

The same pattern repeats at all dimensions of trust as presented at Table 22. A Human advisor is trusted more than the AI for emotional trust (M = 5.90 vs. M = 5.07), as well as for cognitive trust ability (M = 5.78 vs. M = 5.20), for cognitive trust integrity (M = 5.61 vs. M = 4.99), and for cognitive trust benevolence (M = 5.65 vs. M = 4.99). Hence, both H3a and H4a are supported.

Table 22. Descriptive Results of Trust Dimensions - Study 2

		N	Mean	Std. Deviation	Std. Error
Emotional Trust	AI	153	5.074	1.458	.118
	Human	188	5.899	1.308	.095
Cognitive Trust Ability	AI	153	5.199	1.353	.109
	Human	188	5.779	1.355	.099
Cognitive Trust Integrity	AI	153	4.992	1.405	.114
	Human	188	5.606	1.399	.102
Cognitive Trust Benevolence	AI	153	4.987	1.510	.122
	Human	188	5.645	1.398	.102

However, repeating the same study with recommendation type as the single one independent variable shows nonsignificant results at all factors.

In order to check for any combined effect of recommendation source and recommendation type together, univariate analysis are realized by taking both of them as fixed factors whereas emotional trust and each cognitive trust dimension becomes separately the single dependent variable. However, a combined interaction effect of recommendation source and recommendation type is not significant for any one dimension of trust. In other words, type of recommendation is insignificant to influence any type of trust difference credited to AI and Human advisors. Hence, both H3b and H4b are not supported.

5.4.3 Study 3: AI vs. Human - advisor differentiation in evaluating recommendation usefulness and ease of use

H5a: Perceived ease of use in getting a recommendation is higher when the recommendation source is Human

H5b: The difference of perceived ease of use in getting a recommendation between AI and Human advisors shall be influenced by the recommendation type

H6a: Perceived usefulness of a recommendation is higher when the recommendation source is Human

H6b: The difference of perceived usefulness of a recommendation between AI and Human advisors shall be influenced by the recommendation type

To understand the change of perceived usefulness and perceived ease of use in different recommendation source and recommendation type conditions, a MANOVA analysis is realized. Recommendation source and recommendation type are kept as the fixed factors, whereas perceived ease of use and perceived usefulness get to be the dependent variables.

The data is appropriate for a MANOVA analysis with the cell numbers being higher than the number of dependent variables, similar across the conditions, and higher than the practical suggestion of 20 per condition (Hair et al., 2010).

As MANOVA is specifically sensitive to outliers, the Cook' distance is checked for all dependent variables. Except two observations all remain below the threshold of 0.5 (Pennstate, 2018). To be safe from the influence of these two outliers, they are deleted. At the next step, normality is checked both visually and statistically. Although normality could not be assured by statistical analysis neither by Kolmogorov - Smirnov nor by Shapiro-Wilk criteria, the visual check by $Q = Q$ plots showed no highly problematic issues for either one of the variables. In addition, as the sample size is high, data is considered as normal.

The variables are significantly correlated as shown at Table 23 and Table 24.

Table 23. KMO and Bartlett's Test - Study 3

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	457.062
	df	1
	Sig.	.000

Table 24. Correlations - Study 3

		Perceived Ease of Use	Perceived Usefulness
Perceived Ease of Use	Pearson Correlation	1	.861
	Sig. (2-tailed)		.000
Perceived Usefulness	Pearson Correlation	.861	1
	Sig. (2-tailed)	.000	

Unfortunately, the assumption of homoscedasticity between the groups could not be ensured. Although at the univariate level, there is homogeneity between AI and Human advisor conditions, the Box's M test is significant, indicating a non-existence of homoscedasticity on the variables collectively as presented at Table 25 and Table 26 (Hair et al., 2010).

Table 25. Equality of Error Variances - Study 3

	F	*df1*	*df2*	Sig.
Perceived Ease of Use	1.170	7	333	.319
Perceived Usefulness	1.236	7	333	.282

Table 26. Equality of Covariance Matrices - Study 3

Box's M	36.508
F	1.704
df1	21
df2	330169.218
Sig.	.023

Hence, the MANOVA study could not be realized further. As a remedy, recommendation source and recommendation type are taken separately as a single fixed factor and each one's impact on perceived ease of use and perceived usefulness is analyzed by ANOVA.

In relation to the recommendation source, ANOVA analysis uses perceived ease of use and perceived usefulness as the dependent variables and recommendation source as the fixed factor.

Equality of variance is ensured by a nonsignificant Levene's test as presented at Table 27.

Table 27. Homogeneity of Variances - Study 3

	Levene Statistic	*df1*	*df2*	Sig.
Perceived Ease of Use	.095	1	339	.759
Perceived Usefulness	.335	1	339	.563

As presented at Table 28, there is a significant difference between AI and Human advisors. The impact of recommendation source is significant for perceived ease of use (F = 10.336, p = .001) and for perceived usefulness (F = 17.139, p = .000).

Table 28. ANOVA - Study 3

		Sum of Squares	*df*	Mean Square	*F*	Sig.
Perceived Ease of Use	Between Groups	19.339	1	19.339	10.336	.001
	Within Groups	634.273	339	1.871		
	Total	653.612	340			
Perceived Usefulness	Between Groups	32.242	1	32.242	17.139	.000
	Within Groups	637.715	339	1.881		
	Total	669.957	340			

When a recommendation is received from a Human advisor, respectively the perceived ease of use and the perceived usefulness is higher (M = 5.87 and M = 5.87) compared to AI (M = 5.39 and M = 5.25) as presented at Table 29. Hence, both H5a and H6a are supported.

Table 29. Descriptive Results of PEoU and PU - Study 3

		N	Mean	Std. Deviation	Std. Error
Perceived Ease of Use	AI	153	5.390	1.358	.110
	Human	188	5.869	1.376	.100
Perceived Usefulness	AI	153	5.251	1.387	.112
	Human	188	5.869	1.359	.099

In order to check for any combined effect of recommendation source and recommendation type together, univariate analysis are realized by taking both of them as fixed factors whereas perceived ease of use and perceived usefulness become separately the single dependent variable. However, a combined interaction effect of recommendation source and recommendation type is not significant at any of them. In other words, the perceived ease of use and perceived usefulness are higher for a Human advisor at all types of recommendations. Hence, both H5b and H6b are not supported.

5.4.4 Study 4: AI vs. Human - expanded TAM model

H7: Cognitive trust to the recommendation source positively influences emotional trust to the recommendation source

H8: Cognitive trust to the recommendation source positively influences perceived usefulness of the recommendation received

H9: Emotional trust to the recommendation source positively influences the perceived usefulness of the recommendation received

H10: Perceived ease of use in getting a recommendation positively influences cognitive trust to the recommendation source

H11: Perceived ease of use in getting a recommendation positively influences emotional trust to the recommendation source

H12: Perceived ease of use in getting a recommendation positively influences perceived usefulness of the recommendation

H13: Perceived usefulness of the recommendation positively influences the intention to adopt the recommendation

After comparing the two advisors, the pieces of the puzzle are set into a SEM analysis as presented at Figure 9. Thereby the adoption of recommendation is studied within the perspective of TAM; the impacts of different dimensions of trust are observed; the structural difference between AI and Human advisors are checked; and the reasons of such a difference are analyzed.

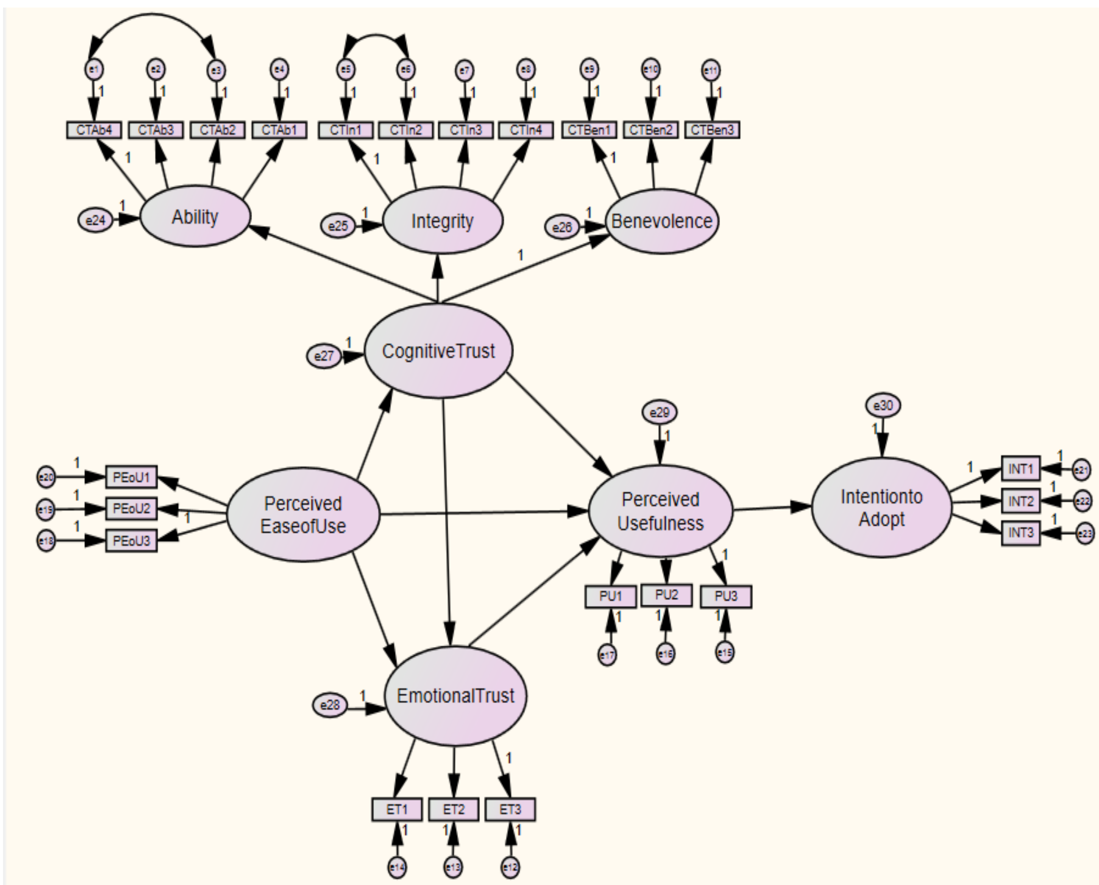


Figure 9. Research model at SEM

Using the whole data together, the results show that the model provided a Chi-square (χ^2) value of 674.867 with 218 degrees of freedom and a p value of .000. A significant χ^2 shows the estimated and observed covariance matrices do not match. However, taking the sample size and the number of the observed variables into consideration, a significant *p* value is expected (Hair et al., 2010).

Rule of thumb states that at least one absolute and one incremental fit index shall be audited (Hair et al., 2010). In terms of absolute fit indices, RMSEA is checked first. RMSEA for the model is .079 and values up to .080 can be considered as acceptable (Hair et al., 2010). SRMR is .047, hence below the conservative guideline of .080 (Hair et al., 2010). On the other hand, the normed χ^2 is 3.1 and remains within the accepted limits of 2.0 and 5.0 (Hair et al., 2010).

In terms of incremental fit indices, CFI, the mostly used index, is .959, i.e. above the threshold of .920 for the given variable number and sample size (Hair et al., 2010). Similarly, other incremental fit indices, NFI and RFI are above the cut off level of .920.

Hence, the overall model shows a good fit as summarized in the Table 30.

Table 30. Fit Indices for All Data - Study 4

Chi-square (χ^2)	
Chi-square	= 674.867
Degrees of freedom	= 218
Probability level	= .000
Absolute Fit Indices	
RMSEA	= 0.079
SRMR	= 0.047
Normed χ^2	= 3.096
Incremental Fit Indices	
CFI	= 0.959
NFI	= 0.940
RFI	= 0.931

In respect to the relationship between the variables, the significance of regression weights are checked. As Table 31 shows, there is one insignificant relationship, namely between perceived ease of use and emotional trust. Other relations are significant and positive; hence, H7, H8, H9, H10, H12, and H13 are supported, while H11 is rejected.

Table 31. Regression Weights for All Data - Study 4

				Unstandardized Estimates	Standardized Estimates	P
H7	Emotional Trust	<---	Cognitive Trust	.821	.811	***
H8	Perceived Usefulness	<---	Cognitive Trust	.226	.234	.003
H9	Perceived Usefulness	<---	Emotional Trust	.291	.305	***
H10	Cognitive Trust	<---	Perceived Ease of Use	.866	.860	***
H11	Emotional Trust	<---	Perceived Ease of Use	.118	.116	.069
H12	Perceived Usefulness	<---	Perceived Ease of Use	.455	.469	***
H13	Intention to Adopt	<---	Perceived Usefulness	.862	.835	***

To check a comparative model, the existing model is extended by adding direct impact of cognitive trust and emotional trust on intention to adopt. However, the results show a Heywood case for AI. A Heywood case, where the standardized regression weights are higher than one, is not logical since it indicates that more than 100% can be explained at the dependent variable. A Heywood case is not expected at studies with a sample size greater than 300 and where all latent variables have at least three observable items, and although a fit can be observed, the solution is improper (Hair et al., 2010).

Previous studies ensured model fit and hypotheses testing for the whole of data. In order to investigate whether these results apply specific for AI and Human advisor condition samples, data is divided according to the recommendation source and the model is rerun simultaneously for both groups. The Chi-square (χ^2) value is 1162.7874 with 436 degrees of freedom and a *p* value of .000. RMSEA for the model is .070, SRMR is .065, and normed χ^2 is 2.7, CFI is .935, NFI is .901, and RFI is .885. Hence, the overall model shows a good fit as summarized at Table 32.

Table 32. Fit Indices after Division of Data to AI and Human Advisors - Study 4

Chi-square (χ^2)	
Chi-square	= 1162.787
Degrees of freedom	= 436
Probability level	= .000
Absolute Fit Indices	
RMSEA	= .070
SRMR	= .065
Normed χ^2	= 2.667
Incremental Fit Indices	
CFI	= .935
NFI	= .901
RFI	= .885

As these values in majority are worse compared to the results achieved without dividing the sample, the moderation according to the recommendation source is evident (Hair et al, 2010).

To comment on the standardized regression weight differences of AI and Human advisors on specific paths, structural weights are constrained and the analysis is rerun.

The comparison between an unconstrained model and structural weights constrained model shows that there is a significant difference as presented at Table 33. In other words, the differences observed at the standardized regression weights are significant.

Table 33. Structural Weights Comparison - Study 4

Model	*df*	CMIN	*p*
Structural weights	48	83.0343	.001

The path specific differences are analyzed by keeping each time one particular path constrained, while leaving the other ones free, and then comparing the results to the unconstrained model. The analyzes show that AI and Human advisor conditions significantly differ at the paths between cognitive trust to perceived usefulness and emotional trust to perceived usefulness, whereas other relationships do not show a significant difference as presented at Table 34.

Table 34. Path Significance Comparison of AI and Human Advisors - Study 4

Model	*df*	CMIN	*p*
Constraining PEoU ► PU	1	1.4546	.228
Constraining PEoU ► CT	1	.0219	.882
Constraining PEoU ► ET	1	.1882	.664
Constraining CT ► ET	1	.0349	.852
Constraining CT ► PU	1	3.9352	.047
Constraining ET ► PU	1	10.7843	.001
Constraining PU ► INT	1	.0295	.864

When comparing the paths in detail, this difference is clarified. Whereas at the whole model only one path is insignificant (PEoU ► ET), division of data into the two conditions of the recommendation source causes two other paths becoming insignificant as well.

Table 35 shows the significance of regression weights for AI and Human advisor conditions at different paths. The two groups show a discrepancy in paths CT ► PU and ET ► PU. Perceived usefulness is not significantly impacted by the cognitive trust for the recommendations received from Human advisor (*p* = .487), on the other hand it is not significantly impacted by the emotional trust for the recommendations received from AI (*p* = 855). Hence, whereas for Human advisors H8 is not supported, for AI H9 is not supported.

Table 35. Path Regression Weights of AI and Human Advisors - Study 4

				AI		Human	
				Standardized Estimates	*p*	Standardized Estimates	*p*
H7	Emotional Trust	<--	Cognitive Trust	.834	***	.847	***
H8	Perceived Usefulness	<--	Cognitive Trust	.458	***	.087	.487
H9	Perceived Usefulness	<--	Emotional Trust	.021	.855	.469	***
H10	Cognitive Trust	<--	Perceived Ease of Use	.821	***	.903	***
H11	Emotional Trust	<--	Perceived Ease of Use	.112	.176	.062	.571
H12	Perceived Usefulness	<--	Perceived Ease of Use	.554	***	.430	***
H13	Intention to Adopt	<--	Perceived Usefulness	.797	***	.854	***

The models are presented separately for AI and Human advisor condition data groups at Figure 10 and Figure 11.

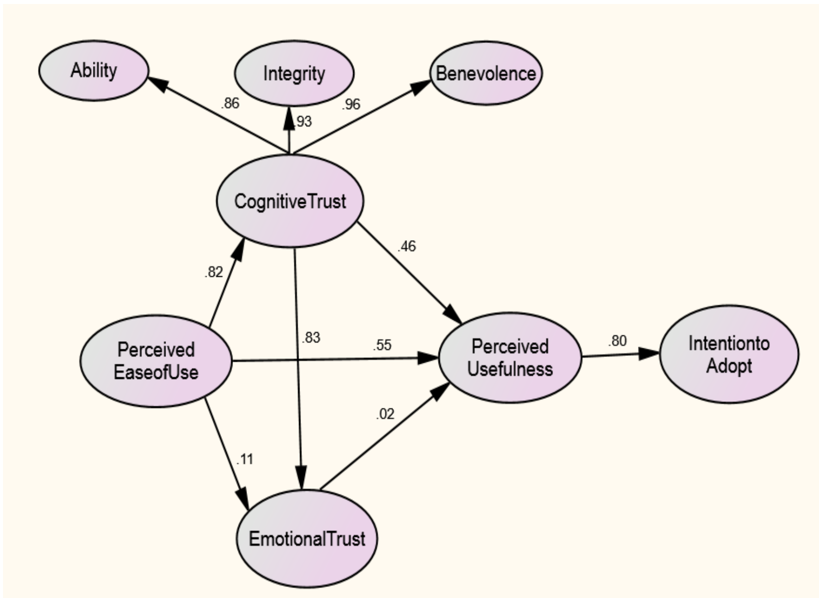


Figure 10. SEM results for AI advisor

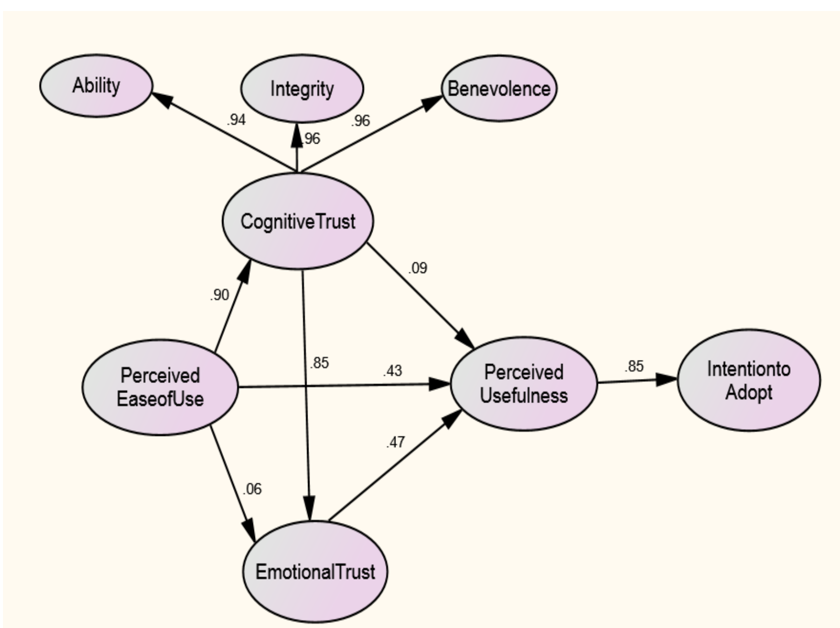


Figure 11. SEM results for Human advisor

To check the impact of mediations, an estimand plugin is utilized by bootstrapping 200 samples with 90% confidence level.

The results reflect the analysis without mediation as presented at Table 36. PEoU ► ET is not significant for any group; ET ► PU is not significant for AI, and CT ► PU is not significant for Human advisor, whereas all others maintain their significance. Hence, there is no full mediation.

Table 36. Mediation Check - Study 4

			AI	Human
			p	*p*
Emotional Trust	<---	Cognitive Trust	***	***
Perceived Usefulness	<---	Cognitive Trust	***	.487
Perceived Usefulness	<---	Emotional Trust	.855	***
Cognitive Trust	<---	Perceived Ease of Use	***	***
Emotional Trust	<---	Perceived Ease of Use	.176	.571
Perceived Usefulness	<---	Perceived Ease of Use	***	***
Intention to Adopt	<---	Perceived Usefulness	***	***

In terms of partial mediation, there are significant indirect effects at PEoU --> PU --> INT and at PEoU --> CT --> ET for both groups. Separately, a significant indirect effect is observed at PEoU --> CT --> PU --> INT for AI and at PEoU --> CT --> ET --> PU --> INT for Human advisor condition. Results are presented at Table 37.

Combining direct and indirect effects, the analysis shows that all variables have a higher impact on intention to adopt for Human advisor compared to AI as presented at Table 38 and Table 39. Especially a very big difference is created by emotional trust. In particular, the impact of emotional trust on intention to adopt is .401 for Human advisor condition whereas it remains as .016 for AI.

Table 37. Partial Mediation - Study 4

	AI		Human	
	Standardized Estimates	*p*	Standardized Estimates	*p*
PEoU --> PU --> INT	.754	.003	.347	.031
PEoU --> CT --> PU	.370	.059	.075	.864
PEoU --> CT --> PU --> INT	.320	.049	.063	.805
PEoU --> ET --> PU	.002	.702	.027	.440
PEoU --> ET --> PU --> INT	.002	.721	.023	.471
PEoU --> CT --> ET	.727	.026	.714	.007
PEoU --> CT --> ET --> PU	.014	.833	.341	.038
PEoU --> CT --> ET --> PU --> INT	.012	.833	.289	.038
CT --> ET --> PU	.016	.833	.388	.061
CT --> ET --> PU --> INT	.014	.833	.330	.043
CT --> PU --> INT	.370	.043	.072	.824
ET --> PU --> INT	.017	.833	.406	.077

Table 38. Standardized Total Effects for AI Advisor - Study 4

	Cognitive Trust	Emotional Trust	Perceived Usefulness	Intention to Adopt
Perceived Ease of Use	.821	.798	.946	.754
Cognitive Trust	0	.834	.475	.379
Emotional Trust	0	0	.021	.016
Perceived Usefulness	0	0	0	.797

Table 39. Standardized Total Effects for Human Advisor - Study 4

	Cognitive Trust	Emotional Trust	Perceived Usefulness	Intention to Adopt
Perceived Ease of Use	.903	.827	.897	.766
Cognitive Trust	0	.847	.485	.414
Emotional Trust	0	0	.469	.401
Perceived Usefulness	0	0	0	.854

The difference between AI and Human advisors, created by the emotional trust becomes visually obvious, when the model is redesigned by eliminating the non-significant paths. According to the path significance results, PEoU ► ET path is omitted for both groups. In specific for each group, the path of ET ► PU is eliminated at AI condition and the path of CT ► PU is eliminated at Human advisor condition.

The updated models demonstrate that for AI emotional trust becomes a dead end and gets useless to affect intention to adopt the recommendation. For Human advisor condition on the other hand, although cognitive trust loses its direct connection to perceived usefulness and hence to intention to adopt, it is still effective through the connection over emotional trust. The models separately for AI and Human advisors are presented at Figure 12 and Figure 13.

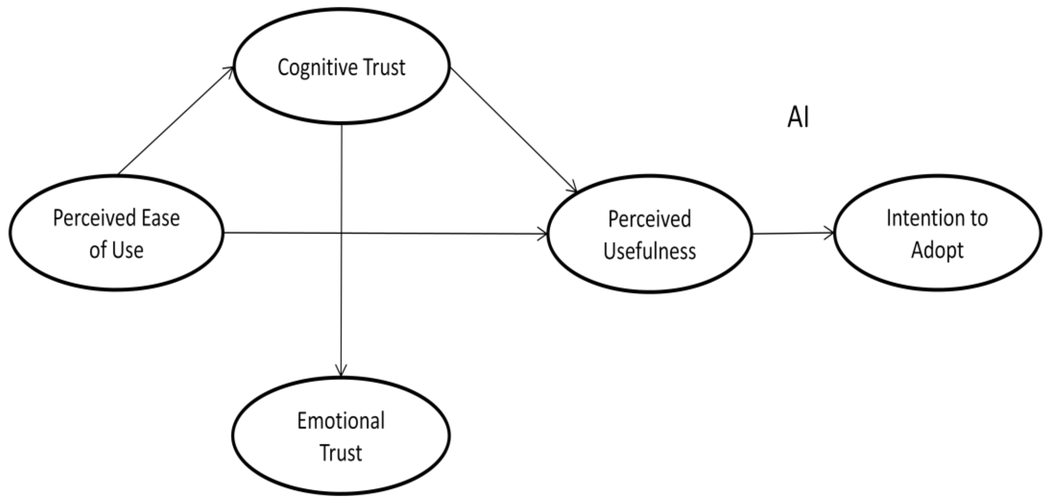


Figure 12. Resulting model for AI advisor

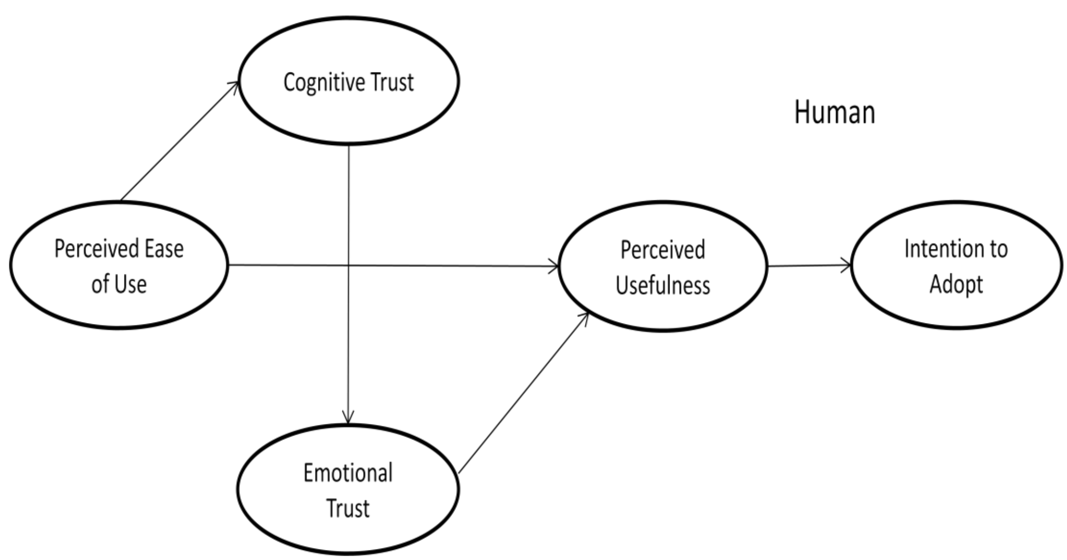


Figure 13. Resulting model for Human advisor

CHAPTER 6

DISCUSSION

The study aimed to test consumers' AI acceptance through a well-known and familiar AI example, recommendations at online shopping. Specifically, intention to adopt the recommendation received from AI is challenged against the intention to adopt the recommendation received from another resource, a Human advisor. The results of this challenge are studied in detail to understand the dynamics behind. In addition, the scope of the recommendations is gradually enhanced in order to audit the changes within the adoption and thereby predict consumer reaction to future potential AI developments.

Results indicate that a Human advisor is preferred over AI. When the same recommendation is received from a fashion designer, it has a higher chance of being accepted. This finding contributes to the algorithm aversion literature (Castelo et al., 2019; Dietvorst, 2016; Dietvorst et al., 2015; Luo et al., 2019; Önkal et al., 2009; Promberger & Baron, 2006; Yeomans et al., 2019). Additionally, it reflects the practical applications, where companies choose to name their AI application as less scary (Hengstler et al., 2016) or to stress the human touch within the loop (Lake, 2018; Stitch Fix, n.d.).

This result shall not be considered as a contradiction to the literature questioning recommendation effectiveness. For AI condition, the paths within the extended TAM model are all in positive direction, i.e. in line with the literature and with the actual sales results indicating that recommendations are appreciated at online shopping (e.g. Accenture Personalization Pulse Check, 2018; Banker & Khetani, 2019; Häubl &Trifts, 2000; Leavitt, 2006; Love, 2014). In other words, it cannot be said that recommendations at online shopping are neglected, however they struggle when being challenged against a Human advisor.

Algorithm aversion was expected at some level of the analysis as the design of the study was arranged accordingly. While Human advisor is not favored by not emphasizing or describing the expertise (Önkal et al., 2009), mitigating effects of algorithm aversion are avoided as well. A subjective domain is selected (Castelo et al., 2019) and any confounding factors on the decision like explanation (Yeomans et. al, 2019) or personalization (Longoni et al., 2019; Whang & Im, 2018) are omitted.

Although algorithm aversion was expected, it was considered to start at a later phase than the simple basic recommendations, and the question was when and why. Since the selected AI application, online shopping recommendation is a very well known and familiar concept within the daily life; AI effect could have been at work and AI could be accepted as capable as a Human advisor at such a trivial step (Haenlein & Kaplan, 2019). Unfortunately, results did not support the hypothesis. Starting with the very basic one, the preference of a fashion designer is stable over all types of recommendations.

Within the study, the result of no impact of recommendation type could be caused due to the general bias against AI being active at all levels (Luo et al., 2019) or due to the domain selected, namely fashion, surpassing the threshold of subjectivity already from the very basic recommendation level (Castelo et al., 2019) or whereas an AI recommendation is familiar, a designer advice could have been evaluated as interesting and valuable.

The studies of Jago (2019) and Köbis and Mossink (2021) can deliver specific insights for the design recommendation, the most subjective one, being not significantly different from the others. In comparing the feedback to creativity related jobs like composing music, creating a recipe, or designing a restaurant concept, Jago (2019) reported that there is not any difference between AI and Human advisors in relation with type-authenticity, i.e. how the resulting piece of work is evaluated. Köbis and Mossink (2021) supported irrelevance of AI aversion specifically at creativity and emphasized the importance of the resulting piece of work. Poems written by humans are preferred against the ones written by an algorithm, but this preference is not impacted when the participants are informed about the author (Köbis & Mossink, 2021). In other words, at the very creative and human specific domain of poetry, the preference between AI and Human is not disturbed further by the transparency of the poet. Accordingly, within this study it could have been that the information of AI activity at design did not create an extra aversion. Another point of view states that an artwork may be presented as created by AI, however people would still acknowledge the role of humans within the process providing both artistic and technological support (Epstein et al., 2020). Hence, design option within the study could have been evaluated as not realized by AI only but with the support of fashion designers. Social presence measured high at AI condition supports this approach as well.

The reasons behind the preference of a Human advisor are questioned at the next steps. First of all, the two recommendation sources enjoy different levels of cognitive trust and emotional trust, and in addition, the perceived ease of use in getting a recommendation and perceived usefulness of the received recommendations varies between them.

In terms of cognitive trust, the study showed that AI remains behind a Human advisor at all factors, namely at ability, integrity, and benevolence. People could have doubts concerning the competency and skills of AI when compared to a fashion designer, who would be taken as the default advisor in fashion (Dietvorst et al., 2015; Dietvorst, 2016). In addition, the recommendation of a designer could be further questioned in terms of rationality, like why a specific sneaker model is recommended, whereas AI is considered as lacking this explanation possibility (Önkal et al., 2009; Yeomans et al., 2019). Benevolence of AI could have been shaken by the questioned goodwill of AI developments in general, and online shopping in specific (Dastin, 2018; Logg et al., 2019; Mirsky & Lee, 2021; Xu & Xiao, 2018).

On the other hand, emotional trust covers the feelings of overall relying to the other party (McKnight & Chervany, 2001). The study showed that relying on a fashion designer for a style advice does create feelings of security, content, and comfort, all being higher compared to AI. Possibly, a person could not be able to clarify why she is feeling a discomfort in depending to AI recommendation, which she meets every day at online shopping, or in contrary why a fashion designer earns a higher overall reliance. As an attitude, emotional trust does not cover rationality (Komiak & Benbasat, 2004, 2006). The feelings of estrangement against an AI advisor (Kim et al., 2016), the lack of social presence (Aksoy et al., 2006; Fulk et al., 1987; Gefen & Straub, 2004; Kumar & Benbasat, 2006), or the emotional incapability of AI (Longoni et al., 2021) can affect the overall dependence.

As a third asset in favor of a Human advisor, if the recommendation is received from a Human advisor, the process is perceived easier. Structuring ease of use of an automatically delivered recommendation by clarity (Koufaris, 2002; Lee & Lee, 2009), participants evaluated the experience with AI as being more opaque, whereas receiving a style recommendation from a fashion designer is more clear and understandable.

Particularly for example, it could be that they could not figure out what kind of a combination will be realized with the offered backpack. However perceived humanness of and similarity with the fashion designer could have led to developing speculations what the mentality of the designer could have been (Aksoy et al., 2006; Gai & Klesse, 2019; Nikolaeva & Sriram, 2006).

And lastly, when a recommendation is received from a Human advisor, it is considered as more useful. The usefulness of a fashion recommendation, in other words the help in shopping effectiveness, should depend on the perceived taste similarity. As AI lacks humanness, its tastes are dissimilar and hence its recommendations are perceived as less useful (Gai & Klesse, 2019; Nikolaeva & Sriram, 2006).

Hence, concerning cognitive trust, emotional trust, perceived ease of use, and perceived usefulness Human advisor is armed much better at the starting point of the race compared to AI. The way these assets operate within the next steps and influence directly and indirectly the dependent variables of the analysis, shows how the race proceeds and why the winner becomes the Human advisor. For this purpose, the study used a TAM model extended with cognitive and emotional trust.

The relationships in between TAM variables, namely between perceived ease of use, perceived usefulness and intention to adopt reflect the literature using TAM in online shopping (Benbasat & Wang, 2005; Gefen et al., 2003; Lee & Lee, 2009). If a recommendation is evaluated as clear, it is considered as being more useful; and the more useful a recommendation is the higher its adoption will be.

Checking the input of the trust dimensions, the first observation is in regard of the relationship between cognitive trust and emotional trust. The results showed that this relationship is in line with the literature for both recommendation sources (Wang et al., 2016). Believing that the recommendation source is skilled, unbiased and has a goodwill led to an increased overall dependence on it (McKnight & Chervany, 2001).

When the relationships between TAM variables and trust dimensions are questioned, it is observed that, for both recommendation sources, the relationship of perceived ease of use is as hypothesized with cognitive trust but is not with emotional trust. A recommendation process perceived as understandable leads to a higher cognitive trust to the source. When everything is transparent, the recommendation receiver considers the source as being confident of own capability, not having a hidden agenda, and not trying to utilize a bias. Accordingly, the literature shows that increasing transparency through explanations brings in positive reaction to recommendation (Wang, et al., 2016; Yeomans et. al, 2019; Zhang & Curley, 2018). In practical, the online shopping platforms increase customer's perceived agency by informing why a specific recommendation is delivered or by providing the possibility to manage recommendations (Cukier, 2021). However, results did not show a significant impact of perceived ease of use on emotional trust. There is no direct effect of perceived ease of use on emotional trust, but an indirect one over cognitive trust. In other words, transparency of the recommendation shall first contribute to the source competency and good intentions. Only if this rational assurance is reached, the shopper can build up the feeling of an overall reliance, which is in line with TRA (Fishbein & Ajzen, 1975).

On the other hand, the relationship between trust dimensions and perceived usefulness delivered interesting insights. Literature states that cognitive trust and emotional trust are asymmetric on recommendation adoption (Komiak & Benbasat, 2004). Although not hypothesized, such an asymmetry emerged at the analysis concerning the recommendation source, when focus is put on the impact on perceived usefulness of the recommendation.

For AI, emotional trust appeared to be insignificant in its relationship to perceived usefulness. In following, for AI condition emotional trust does not influence any other variable in the model, i.e. the flow of the model is stuck at that point. For AI condition, the path through cognitive trust becomes the only source of impact.

Similarly, for Human condition, cognitive trust appeared to be insignificant on perceived usefulness. Nevertheless, in spite of the AI condition, cognitive trust does not become useless; it is still in the game through the impact over emotional trust. In other words the believes on ability, integrity, and benevolence specifications of a fashion designer are still important through their impact on the overall dependence felt to her.

Another perspective reinforces that emotional trust is a breaking point in differentiating AI and Human advisors. When direct and indirect effects are considered in total, it is observed that for all variables, AI suffers at impact on intention to adopt the recommendation. In specific, compared to a Human advisor, at AI condition the impact of cognitive trust on intention to adopt is lower, as well as the impacts of perceived ease of use and perceived usefulness. However, whereas emotional trust is as important as cognitive trust for Human advisor condition, it is a dead end for AI. This deficiency of AI also explains the decreased algorithm aversion result reported in the literature when AI is used to augment a human (Longoni et al., 2019) as in such a case, the human is supplying the lacking emotional trust. The perceived incapability of AI in emotions is in line with the findings of Longoni et al. (2021). In summary, people do not feel as content, comfortable, and secure to rely on AI as they do on a Human advisor; and even if they had felt so, it would not influence their decision whether or not to adopt the recommendation received.

The role of emotions within the consumption experience is stressed by the seminal work of Holbrook and Hirschman (1982) and online shopping is not different (Trevinal & Stenger, 2014). Online shopping experience is described as lacking fun and social interaction (Helm, Kim, & Van Riper, 2020) and as consumers' reliance on emotions and social relations are increasing within the enhancing digital life, the emotional appeal shall become more fundamental (Huang et al., 2019). Especially depending on the specific needs, the role of emotions can become more dominant. Dawar and Bendle (2018) gave just the product of the study as the example to stress this predominance of emotions and stated that "While shopping for shoes may be fun, picking the right toothbrush from more than 200 products is pretty tedious." Hence receiving a sneaker recommendation from AI may be harming fun, but a communication with a designer may enhance it. CEO of Stitch Fix, a company providing online style combination proposals where designers retouch the offers preselected by AI, states that a designer is able to assess the specialty of a person's need, to build up a connection with her, and to deliver much more than a perfectly fitting style (Lake, 2018). Within the scope of this study, this statement can be translated as while AI is capable of a style combination, i.e. assuring cognitive trust, a designer can offer more, i.e. appealing to emotions.

From a broader point of view, the positioning of AI and Human advisors in regard of emotional trust is in line with the literature questioning the job market changes. Big technology breakthroughs like AI always frightened people about losing their jobs, however developments in AI are expected to create new ones (Acemoglu & Restrepo,

2018) specifically in intuitive and empathetic domains (Huang & Rust, 2018). In other words, AI shall take place at more cognitive oriented jobs and leave emotion oriented ones to humans (Huang et al., 2019).

CHAPTER 7

CONCLUSIONS, IMPLEMENTATIONS, LIMITATIONS

It is necessary to get one-step away from a functional evaluation of AI and to develop an understanding of the related consumer experience from psychological and sociological perspectives (Puntoni, Reczek, Giesler, & Botti, 2021).

This study focused on AI from a marketing point of view and questioned how people perceive AI in a comparison with a Human advisor. Findings showed that people could not build an overall reliance on AI as high as a Human advisor and have difficulties to understand the process managed by it. In addition, this emotional reaction is observed as being stable at different conditions of AI capability. Therefore, it can be expected that the future developments in AI can face similar feedback. AI can and most probably will increase its competence. However, irrelevant of its performance, in other words irrelevant whether it delivers a simple product recommendation or provides a complete lifestyle design, consumer surrender with a peace of mind shall not be expected unless the emotional concerns are solved.

Theoretically, the study offers a combination of two literature streams, recommendation effectiveness and algorithm adoption. By benefiting the findings of both literature streams and by utilizing the respective different methodologies simultaneously, insights are provided for the consumer perception of AI. In addition, the social role of AI is taken into consideration and the cognitive TAM model is completed with emotional aspects. Thus, algorithm aversion observed in the literature is explained with specific reasons behind the scene. For example, the decrease of algorithm aversion in case of building a team with a human (Longoni et al., 2019) can be explained by the supplied emotional trust thanks to the human partner.

Another theoretical contribution of the study is in a more macro term, specifically by providing clues about AI positioning within the future society. The target of AI technology is to resemble the human intelligence. However, if and when this target would be achieved, the challenge put against human position within different stages of life becomes a concern. The question finds both positive and negative answers in literature, which describe utopian and dystopian futures respectively (Kaplan & Haenlein, 2020). This study supports the idea that society will be capable to adapt to a future with AI (Acemoglu & Restrepo, 2018; Huang et al., 2019), as humans have indispensible capabilities where AI is lacking. In other words, it is not that humans are temporarily somewhat better than AI and that this gap can close when AI develops further. The study suggests that a whole domain of the emotional world belongs to human.

In managerial terms, it can be said that companies utilizing AI technology within consumption realm have to consider the emotional feedback of people. When AI is compared to Human, in spite of being functionally superior, it can still face an aversion. Therefore, a focus only on the technological development of AI is not sufficient to take full advantage of it.

In addition, when utilizing AI, companies need to explain the process to their customers to increase transparency. Within this regard, they can also support initiatives like explainable AI or deep fake control, as otherwise, accumulating news of AI dark side can harm trust built to applications within the consumption realm as well.

Another practical implication could be to utilize AI as an augmenter to the human as offered by Longoni et al. (2019). The companies, practically applying the shipping-then-shopping understanding, i.e. sending items to the potential buyer before there is an actual order, prefer to emphasize the human contribution within their process (Davenport et al., 2020; Lake, 2018). Depending on this study, it can be stated that this is a good strategy, because in this way, they are able to deliver the lacking emotional trust and make the process more understandable for the customer.

This study has several limitations. First, it focused on a feedback to a pure AI, in other words AI strengths are not put forward. The aim had been to discuss the impact of other variables like trust and to observe the change at a gradual empowerment of AI. However, the deliberately not used potential saviors of AI such as personalization, explanation, objectivity of domain, and control power can change the power play between AI and Human advisor (Castelo et al., 2019; Dietvorst et al., 2018; Longoni et al., 2019; Whang & Im, 2018; Yeomans et. al, 2019). Hence, further studies can challenge the results of the study by manipulating these characteristics. Their impact can then be followed at the differentiation between AI and Human advisors and especially at the impact on emotional trust. The observations can help to come up with new ideas in how to support AI adoption.

In addition, the study is capable to reflect a real online shopping experience only from a limited perspective. First of all, it uses a hypothetical setting with a vignette, proposes alternatives limited in terms of number and model, delivers no detailed information, and misses price data. Then, the study only asks intention to adopt and does not follow up a purchase. Third, an immediate feedback of intention is interrogated; since the study is realized at one shot and extra thinking time could not be provided to the participants for search, comparison, and consideration. A field study with an online shopping site could be eliminating all these limitations and provide the possibility to observe the reactions within the real life. Such a site offers hundreds of alternative models with necessary extra information. Additionally in this way it would be possible to follow the reactions in a timeframe and monitor page view, item search, actual purchase, and even returns.

APPENDIX A

EXPERIMENT FLOW AND QUESTIONNAIRE (ENGLISH)

Do you make online shopping for apparel items? (Filter)

Yes ↓   *No* → Thanking and ending the study

Imagine that you consider buying a pair of sneakers for the summer. For this purpose you surf on an e-commerce platform, which you never used before and met for the first time. There are several different sneaker models on this e-commerce site. You will see them within a mixed order right now. You do not need to keep the models in mind. Please just think that you surf on the pages of an e-commerce site, have a look at the models, and pass to the next page.

Back Next

Figure A1. Experimental stimuli

Back Next

Figure A2. Experimental stimuli (continued)

Back Next

While you proceed looking at the models, suppose that a pop up message appears

Back Next

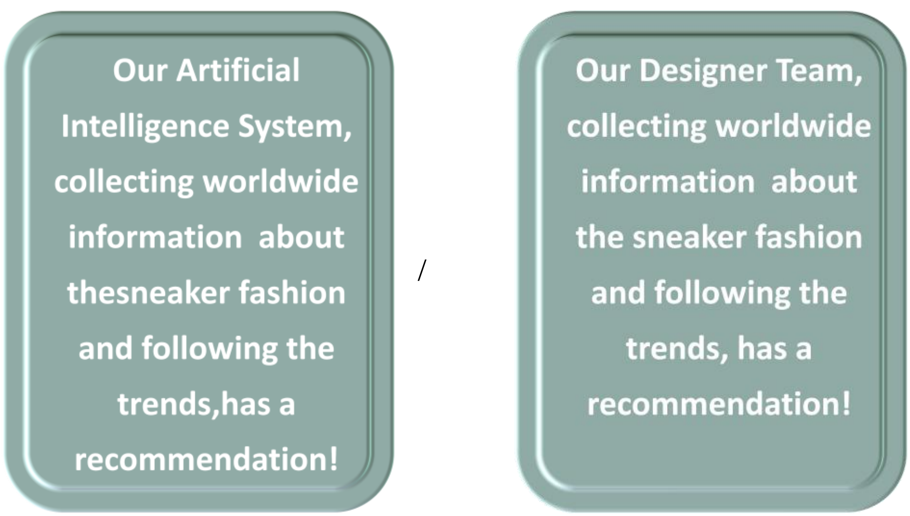


Figure A3. Experiment recommendation source manipulation (English)

Back Next

Figure A4. Experiment recommendation type manipulation (English)

Back Next

While you were checking sneaker models, Artificial Intelligence System (Designer Team) recommended a different model (a model produced with environmentally conscious material but slightly higher in price / a backpack to accompany the sneakers / a model drawn and designed by it). When surfing and shopping on this e-commerce platform, what do you think about this recommendation and similar ones?

1. I am willing to use the recommendations of this Artificial Intelligence System (Designer Team) as an aid to help with my decisions

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

2. I am willing to let the recommendations of this Artificial Intelligence System (Designer Team) assist me in deciding which product to buy

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

3. I am willing to use the recommendations of this Artificial Intelligence System (Designer Team) as a tool that suggests me a number of products

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

Artificial Intelligence System (Designer Team) recommended a different model (a model produced with environmentally conscious material but slightly higher in price / a backpack to accompany the sneakers / a model drawn and designed by it). How do you evaluate this Artificial Intelligence System (Designer Team)?

4. This Artificial Intelligence System (Designer Team) is competent and effective to make recommendations at sportswear category

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

5. This Artificial Intelligence System (Designer Team) gives recommendations very well

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

6. This Artificial Intelligence System (Designer Team) is capable and proficient to make recommendations at sportswear category

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

7. This Artificial Intelligence System (Designer Team) is very knowledgeable at sportswear category in general

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

8. This Artificial Intelligence System (Designer Team) is truthful in its dealings with me

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

9. I would characterize this Artificial Intelligence System (Designer Team) as honest

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

10. This Artificial Intelligence System (Designer Team) keeps commitments

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

11. This Artificial Intelligence System (Designer Team) is sincere and genuine

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

Artificial Intelligence System (Designer Team) recommended a different model. What do you think about this Artificial Intelligence System (Designer Team)?

12. I believe that this Artificial Intelligence System (Designer Team) would act in my best interest

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

13. If I required help, this Artificial Intelligence System (Designer Team) would do its best to help me

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

14. This Artificial Intelligence System (Designer Team) is interested in my well being not just its own

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

15. When making a shopping decision, I feel secure to rely on this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

16. When making a shopping decision, I feel comfortable to rely on this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

17. When making a shopping decision, I feel content to rely on this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

Artificial Intelligence System (Designer Team) recommended a different model (a model produced with environmentally conscious material but slightly higher in price / a backpack to accompany the sneakers / a model drawn and designed by it). What do you think about engaging with and getting recommendations from Artificial Intelligence System (Designer Team)?

18. It is easy to receive recommendations from this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

19. It is clear to receive recommendations from this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

20. It is easy to understand receiving recommendations from this Artificial Intelligence System (Designer Team)

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

21. Using the recommendation received from this Artificial System (Designer Team) can improve my shopping performance

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

22. Using the recommendation received from this Artificial System (Designer Team) can increase my shopping productivity by saving time

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

23. Using the recommendation received from this Artificial System (Designer Team) can increase my shopping effectiveness by finding suitable option

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

24. The recommendation received from this Artificial System (Designer Team) is useful

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

While checking sneaker models, you received a different recommendation (Control)

25. What was the recommendation?

a) *A different model*

b) *A model produced with environmentally conscious material but slightly higher in price*

c) *A backpack to accompany the sneakers*

d) *A model drawn and designed by Artificial Intelligence System (Designer Team) itself*

26. How complicated is it to make such a recommendation?

Very Easy						*Very Difficult*
1	2	3	4	5	6	7

27. Did you feel a sense of human contact within this recommendation process?

Definitely Not Felt						*Definitely Felt*
1	2	3	4	5	6	7

28. Did you feel a sense of human warmth within this recommendation process?

Definitely Not Felt						*Definitely Felt*
1	2	3	4	5	6	7

29. Did you feel a sense of human sensitivity within this recommendation process?

Definitely Not Felt						*Definitely Felt*
1	2	3	4	5	6	7

How do you evaluate yourself at the below points?

30. It is easy for me to trust a person or a thing

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

31. My tendency to trust a person or a thing is high

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

32. I tend to trust a person or a thing, even though I have little knowledge of it

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

33. I feel that some of my characteristics are completely unique to me

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

34. I think that the characteristics that make me up are completely different from others

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

35. I feel unique

Definitely Do Not Agree						*Definitely Agree*
1	2	3	4	5	6	7

We thank you accompanying us within this shopping journey, where Artificial Intelligence System (Designer Team) made a recommendation. Can we get to know you a little better?

36. Are fashion and apparel subjects (footwear, clothing, bag, accessories, watch, eyeglasses) within your interest?

Definitely Not Interested At All						*Definitely Very Interested*
1	2	3	4	5	6	7

37. What is your view frequency on the products at Internet e-commerce platforms? (except grocery shopping and food ordering)

- ☐ *Every day*
- ☐ *3-4 times a week*
- ☐ *1-2 times a week*
- ☐ *2-3 times a month*
- ☐ *1-2 times a month*
- ☐ *Once every two months*
- ☐ *Once every three months or less*

38. What is your purchase frequency at Internet e-commerce platforms? (except grocery shopping and food ordering)

- ☐ *Every day*
- ☐ *3-4 times a week*
- ☐ *1-2 times a week*
- ☐ *2-3 times a month*
- ☐ *1-2 times a month*
- ☐ *Once every two months*
- ☐ *Once every three months or less*

39. How long have you been shopping at Internet e-commerce platforms? (except grocery shopping and food ordering)

- ☐ *Less than one year*
- ☐ *1-2 years*
- ☐ *2-4 years*
- ☐ *4-6 years*
- ☐ *6-8 years*
- ☐ *8-9 years*
- ☐ *More than 9 years*

40. Your gender

- [ ] *Female*
- [ ] *Male*
- [ ] *Do not want to state*

41. Your age: …………

42. Your education

- [ ] *Elementary school graduate or high school student*
- [ ] *High school graduate*
- [ ] *University student*
- [ ] *University graduate*
- [ ] *Master/PhD student*
- [ ] *Master/PhD graduate*

43. Your working status

- [ ] *Student*
- [ ] *Housewife*
- [ ] *Working*
- [ ] *Unemployed*
- [ ] *Retired*

44. Your monthly income

- [ ] *2,000TL or less*
- [ ] *2,001-4,000TL*
- [ ] *4,001-6,000TL*
- [ ] *6,001-8,000TL*
- [ ] *8,001-10,000TL*
- [ ] *10,001TL or more*

APPENDIX B

EXPERIMENT FLOW AND QUESTIONNAIRE (TURKISH)

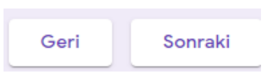
Internet üzerinden giyim ürünleri alışverişi yapar mısınız? (Filtreleme)

Evet ⬇ *Hayır* ➡ Teşekkür ve sonlandırma

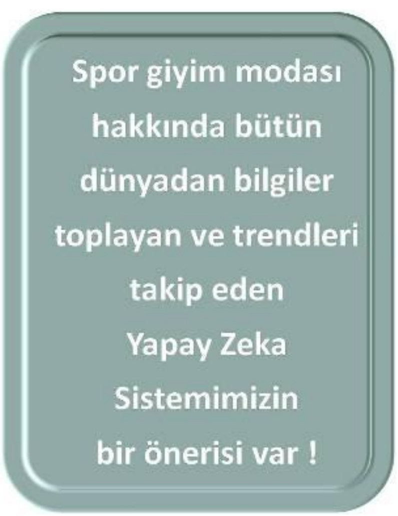
Yaz için günlük bir spor ayakkabı satın almayı düşündüğünüzü ve bu amaçla Internet üzerinde daha önce hiç kullanmadığınız ve ilk defa rastladığınız bir e-ticaret sitesine baktığınızı hayal edin. Bu e-ticaret sitesinde birçok farklı spor ayakkabı modeli var. Bazılarını birazdan karışık bir sırada görmeye başlayacaksınız. Modelleri aklınızda tutmaya çalışmanıza gerek yok. Lütfen sadece herhangi bir e-ticaret sitesinin sayfalarında dolaştığınızı ve modellere bakarak bir sonraki sayfaya geçtiğinizi düşünün.

Figure B1. Experimental Stimuli

Figure B2. Experimental stimuli (continued)



Modellere bakarak ilerlerken karşınıza yeni bir mesaj kutusunun açıldığını varsayın.



/

Figure B3. Experiment recommendation source manipulation (Turkish)

Figure B4. Experiment recommendation type manipulation (Turkish)

Siz spor ayakkabı modellerine bakarken Yapay Zeka Sistemi (Tasarımcı Ekibi) farklı bir model (çevreci malzeme ile üretilen ama biraz daha yüksek fiyatlı bir model / ayakkabı modellerine eşlik edebilecek bir sırt çantası / kendi çizdiği ve tasarladığı bir model) önerdi. Bu e-ticaret sitesinde seçeneklere bakmaya ve alışverişe devam ederken, bu ve benzer öneriler için ne düşünürsünüz?

1. Bu Yapay Zeka Sisteminin (Tasarımcı Ekibinin) önerilerini kararlarımda yardımcı olarak kullanmaya hazırım

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

2. Hangi ürünü almam konusunda karar verirken bu Yapay Zeka Sisteminin (Tasarımcı Ekibinin) önerilerinin bana yardım etmesine izin vermeye hazırım

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

3. Bu Yapay Zeka Sisteminin (Tasarımcı Ekibinin) önerilerini bana ürün tavsiye eden bir araç olarak kullanmaya hazırım

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

Yapay Zeka Sistemi (Tasarımcı Ekibi) farklı bir model (çevreci malzeme ile üretilen ama biraz daha yüksek fiyatlı bir model / ayakkabı modellerine eşlik edebilecek bir sırt çantası / kendi çizdiği ve tasarladığı bir model) önerdi. Bu Yapay Zeka Sistemini (Tasarımcı Ekibini) nasıl değerlendirirsiniz?

4. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) spor giyim kategorisinde öneri vermede yeterli ve etkindir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

5. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) öneri vermede çok iyidir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

6. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) spor giyim kategorisinde öneri vermede yetenekli ve yetkindir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

7. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) genel olarak spor giyim kategorisinde çok bilgilidir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

8. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) benimle ticari ilişkisinde doğru sözlüdür

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

9. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) bence dürüst olarak nitelendirilir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

10. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) söz verdiği şeyi yerine getirir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

11. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) samimi ve içtendir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

Yapay Zeka Sistemi (Tasarımcı Ekibi) farklı bir model önerdi. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) hakkında ne düşünürsünüz?

12. Bu Yapay Zeka Sisteminin (Tasarımcı Ekibinin) bana en çok yarar getirecek şekilde hareket edeceğine inanırım

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

13. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi), yardım istediğim takdirde, bana yardım etmek için yapabileceğinin en iyisini yapacaktır

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

14. Bu Yapay Zeka Sistemi (Tasarımcı Ekibi) benim iyiliğimle ilgilenecektir, sadece kendi iyiliği ile değil

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

15. Alışveriş kararı verirken bu Yapay Zeka Sistemine (Tasarımcı Ekibine) güvenmekle kendimi emniyette hissederim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

16. Alışveriş kararı verirken bu Yapay Zeka Sistemine (Tasarımcı Ekibine) güvenmekle kendimi rahat hissederim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

17. Alışveriş kararı verirken bu Yapay Zeka Sistemine (Tasarımcı Ekibine) güvenmekle kendimi memnun hissederim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

Yapay Zeka Sistemi (Tasarımcı Ekibi) farklı bir model önerdi. Yapay Zeka Sistemi (Tasarımcı Ekibi) ile etkileşime geçme ve öneri alma hakkında ne düşünürsünüz?

18. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) öneri almak kolaydır

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

19. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) öneri almak açık ve nettir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

20. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) öneri almak kolay anlaşılır

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

21. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) aldığım öneriyi kullanmak alışveriş performansımı iyileştirebilir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

22. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) aldığım öneriyi kullanmak hız kazandırarak alışveriş verimliliğimi yükseltebilir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

23. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) aldığım öneriyi kullanmak uygun seçeneği bularak alışveriş etkinliğimi artırabilir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

24. Bu Yapay Zeka Sisteminden (Tasarımcı Ekibinden) aldığım öneri kullanışlıdır

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

Spor ayakkabı modellerine bakarken farklı bir öneri ile karşılaştınız (Kontrol)

25. Gördüğünüz öneri hangisiydi?

a) *Farklı bir spor ayakkabı modeli*

b) *Çevreci malzemeden üretilen ama biraz daha yüksek fiyatlı bir spor ayakkabı modeli*

c) *Ayakkabı modellerine eşlik edebilecek bir sırt çantası*

d) *Yapay Zeka Sisteminin (Tasarımcı Ekibinin) kendisinin çizdiği ve tasarladığı bir spor ayakkabı modeli*

26. Böyle bir öneride bulunabilmek ne kadar zordur?

Çok kolay						*Çok zor*
1	2	3	4	5	6	7

27. Bu öneri sürecinde insani bir iletişim hissettiniz mi?

Kesinlikle hissetmedim						*Kesinlikle hissettim*
1	2	3	4	5	6	7

28. Bu öneri sürecinde insani bir sıcaklık hissettiniz mi?

Kesinlikle hissetmedim						*Kesinlikle hissettim*
1	2	3	4	5	6	7

29. Bu öneri sürecinde insani bir duyarlılık hissettiniz mi?

Kesinlikle hissetmedim						*Kesinlikle hissettim*
1	2	3	4	5	6	7

Kendinizi aşağıdaki konularda nasıl değerlendirirsiniz?

30. Bir şeye veya kişiye güven duymak benim için kolaydır

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

31. Bir şeye veya kişiye güven duymaya eğilimim yüksektir

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

32. Hakkında az bilgim olsa da, bir şeye veya kişiye güvenme eğilimindeyim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

33. Bazı özelliklerimin tamamen bana özgün olduğunu hissederim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

34. Beni oluşturan özelliklerin diğer insanlardan tamamen farklı olduğunu düşünürüm

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

35. Benzersiz olduğumu hissederim

Kesinlikle katılmıyorum						*Kesinlikle katılıyorum*
1	2	3	4	5	6	7

Yapay Zeka Sisteminin (Tasarımcı Ekibinin) bir öneride bulunduğu bu alışveriş yolculuğunda bize eşlik ettiğiniz için çok teşekkür ediyoruz. Sizi biraz daha yakından tanıyabilir miyiz?

36. Giyim ürünleri (ayakkabı, giysi, çanta, aksesuar, saat, gözlük) ve moda ilgi duyduğunuz bir konu mudur?

Kesinlikle hiç ilgili değilim						*Kesinlikle çok ilgiliyim*
1	2	3	4	5	6	7

37. Internet üzerindeki e-ticaret sitelerinde ürünlere bakma ve inceleme sıklığınız nedir? (market alışverişi ve yemek siparişi hariç)

- [ ] *Her gün*
- [ ] *Haftada 3-4 kez*
- [ ] *Haftada 1-2 kez*
- [ ] *Ayda 2-3 kez*
- [ ] *Ayda 1-2 kez*
- [ ] *İki ayda 1 kez*
- [ ] *Üç ayda 1 kez veya daha az*

38. Internet üzerindeki e-ticaret sitelerinde alışveriş yapma sıklığınız nedir? (market alışverişi ve yemek siparişi hariç)

- [ ] *Her gün*
- [ ] *Haftada 3-4 kez*
- [ ] *Haftada 1-2 kez*
- [ ] *Ayda 2-3 kez*
- [ ] *Ayda 1-2 kez*
- [ ] *İki ayda 1 kez*
- [ ] *Üç ayda 1 kez veya daha az*

39. Internet üzerindeki e-ticaret sitelerinde ne kadar süredir alışveriş yapıyorsunuz? (market alışverişi ve yemek siparişi hariç)

- [ ] *1 yıldan az*
- [ ] *1-2 yıldır*
- [ ] *2-4 yıldır*
- [ ] *4-6 yıldır*
- [ ] *6-8 yıldır*
- [ ] *8-9 yıldır*
- [ ] *9 yıldan fazla*

40. Cinsiyetiniz

- [ ] *Kadın*
- [ ] *Erkek*
- [ ] *Belirtmek istemiyorum*

41. Yaşınız: …………

42. Eğitim Durumunuz

- [ ] *İlköğretim mezunu veya lise öğrencisi*
- [ ] *Lise mezunu*
- [ ] *Üniversite öğrencisi*
- [ ] *Üniversite mezunu*
- [ ] *Lisansüstü öğrencisi*
- [ ] *Lisansüstü mezunu*

43. Çalışma Durumunuz

- [ ] *Öğrenci*
- [ ] *Evhanımı*
- [ ] *Çalışıyor*
- [ ] *Çalışmıyor*
- [ ] *Emekli*

44. Aylık net geliriniz

- [ ] *2,000TL ve altı*
- [ ] *2,001-4,000TL*
- [ ] *4,001-6,000TL*
- [ ] *6,001-8,000TL*
- [ ] *8,001-10,000TL*
- [ ] *10,001TL ve üstü*

APPENDIX C

SCALES

Intention to adopt - (adapted from Wang & Benbasat, 2005)

- I am willing to use … as an aid to help with my decisions about which product to buy
- I am willing to let … assist me in deciding which product to buy
- I am willing to use … as a tool that suggests me a number of products

Cognitive trust

Ability - (adapted from Wang et al., 2016)

- ... is competent and effective to make recommendations at sportswear category
- ... gives recommendations very well
- … is capable and proficient to make recommendations at sportswear category
- … is very knowledgeable at sportswear category in general

Integrity - (adapted from Wang et al., 2016)

- … is truthful in its dealings with me
- I would characterize this … as honest
- … keeps commitments
- … is sincere and genuine

Benevolence - (adapted from Wang et al., 2016)

- I believe that this … would act in my best interest
- If I required help, this … would do its best to help me
- This … is interested in my well-being not just its own

Emotional trust - (adapted from Komiak & Benbasat, 2006)

- When making a shopping decision, I feel secure to rely on this …
- When making a shopping decision, I feel comfortable to rely on this …
- When making a shopping decision, I feel content to rely on this …

Perceived ease of use - (adapted from Koufaris, 2002; Lee & Lee, 2009)

- It is easy to receive recommendations from this …
- It is clear to receive recommendations from this …
- It is easy to understand receiving recommendations from this …

Perceived usefulness (adapted from Koufaris, 2002; Lee & Lee, 2009)

- Using the recommendation received from this … can improve my shopping performance
- Using the recommendation received from this … can increase my shopping productivity by saving time
- Using the recommendation received from this … can increase my shopping effectiveness by finding suitable option
- The recommendation received from this … is useful

Social presence - (adapted from Gefen & Straub, 2004)

- Felt a sense of human contact within the recommendation process
- Felt a sense of human warmth within the recommendation process
- Felt a sense of human sensitivity within the recommendation process

Trust propensity (adapted from Wang &Benbasat, 2007)

- It is easy for me to trust a person or a thing
- My tendency to trust a person or a thing is high
- I tend to trust a person or a thing, even though I have little knowledge of it

Need for uniqueness (adapted from Şimşek &Yalınçetin, 2010)

- I feel that some of my characteristics are completely unique to me
- I think that the characteristics that make me up are completely different from others
- I feel unique

APPENDIX D

PROFILE SAMPLE DETAILS

The impact of deleting observations is studied by comparing the deleted and kept observations as presented in Table D1 and Table D2. Except online shopping purchase frequency, deleted and kept observations do not show a significant difference. For online shopping frequency the kept observations shop more (*M* = 3.26) than the deleted observations (*M* = 2.54).

Table D1. Equality of Error Variances

	F	df1	df2	Sig.	Type III Sum of Squares	Sig.
Gender	3.393	1	398	.066	.265[a]	.305
Age	4.499	1	398	.035	4.596[b]	.304
Education	5.267	1	398	.022	.001[c]	.975
Work Status	3.783	1	398	.052	.008[d]	.911
Income	10.315	1	398	.001	2.958[e]	.200
Online Shopping View Frequency	1.012	1	398	.315	3.494[f]	.204
Online Shopping Purchase Frequency	1.385	1	398	.240	26.187[g]	.000
Online Shopping Experience	3.378	1	398	.067	.056[h]	.894

Table D2. Robust Tests of Equality of Means

		Statistic	df1	df2	Sig.
Age	Brown-Forsythe	1.314	1	87.650	.255
Education	Brown-Forsythe	.001	1	72.739	.978
Income	Brown-Forsythe	1.257	1	72.311	.266
Online Shopping Purchase Frequency	Brown-Forsythe	11.794	1	74.985	.001

Table D3. Online Shopping Purchase Frequency Descriptive Statistics

		N	Mean	Std. Deviation
Online Shopping Purchase Frequency	Deleted	59	2.54	1.512
	Not Deleted	341	3.26	1.355

Data normality is presented at Table D4.

Table D4. Normality of Data

		INT1	INT2	INT3	SP1	SP2	SP3
N	Valid	341	341	341	341	341	341
	Missing	0	0	0	0	0	0
Skewness		-.809	-.890	-.878	-.511	-.584	-.550
Std. Error of Skewness		.132	.132	.132	.132	.132	.132
Kurtosis		.031	.191	.011	-.208	-.052	-.286
Std. Error of Kurtosis		.263	.263	.263	.263	.263	.263

Table D4. Normality of Data (continued)

		ET1	ET2	ET3	CTAb1	CTAb2	CTAb3	CTAb4
N	Valid	341	341	341	341	341	341	341
	Missing	0	0	0	0	0	0	0
Skewness		-.783	-.797	-.781	-.845	-.784	-.882	-.778
Std. Error of Skewness		.132	.132	.132	.132	.132	.132	.132
Kurtosis		-.103	-.170	-.177	.036	.039	.254	-.011
Std. Error of Kurtosis		.263	.263	.263	.263	.263	.263	.263

Table D4. Normality of Data (continued)

		CTIn1	CTIn2	CTIn3	CTIn4	CTBen1	CTBen2	CTBen3
N	Valid	341	341	341	341	341	341	341
	Missing	0	0	0	0	0	0	0
Skewness		-.813	-.734	-.616	-.778	-.685	-.600	-.796
Std. Error of Skewness		.132	.132	.132	.132	.132	.132	.132
Kurtosis		.015	-.208	-.320	.063	-.374	-.513	-.116
Std. Error of Kurtosis		.263	.263	.263	.263	.263	.263	.263

Table D4. Normality of Data (continued)

		PEoU1	PEoU2	PEoU3	PU1	PU2	PU3	PU4
N	Valid	341	341	341	341	341	341	341
	Missing	0	0	0	0	0	0	0
Skewness		-.816	-.781	-.907	-.810	-.900	-.885	-.806
Std. Error of Skewness		.132	.132	.132	.132	.132	.132	.132
Kurtosis		-.183	-.365	-.151	-.114	.126	.054	-.064
Std. Error of Kurtosis		.263	.263	.263	.263	.263	.263	.263

Table D4. Normality of Data (continued)

						Online Shopping		
		Age	Education	Work Status	Income	View Frequency	Purchase Frequency	Experience
N	Valid	341	341	341	341	341	341	341
	Missing	0	0	0	0	0	0	0
Skewness		.077	.201	-.658	.385	.966	.125	.386
Std. Error of Skewness		.132	.132	.132	.132	.132	.132	.132
Kurtosis		-1.117	-.448	-.169	-.430	.067	-.418	-.663
Std. Error of Kurtosis		.263	.263	.263	.263	.263	.263	.263

APPENDIX E

EXPLORATORY FACTOR ANALYSIS DETAILS

At first step EFA is run by including all variables; results are presented at Table E1, Table E2, Table E3, and Table E4.

Table E1. All variables - KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.972
	Approx. Chi-Square	11600.535
Bartlett's Test of Sphericity	df	276
	Sig.	.000

Table E2. All variables - Communalities

	Initial	Extraction
INT1	1.000	.919
INT2	1.000	.930
INT3	1.000	.907
ET1	1.000	.910
ET2	1.000	.924
ET3	1.000	.929
CTAb1	1.000	.900
CTAb2	1.000	.903
CTAb3	1.000	.927
CTAb4	1.000	.840
CTInt1	1.000	.885
CTInt2	1.000	.893
CTInt3	1.000	.869
CTInt4	1.000	.858
CTBen1	1.000	.892
CTBen2	1.000	.903
CTBen3	1.000	.886
PEoU1	1.000	.908
PEoU2	1.000	.913
PEoU3	1.000	.917
PU1	1.000	.904
PU2	1.000	.882
PU3	1.000	.911
PU4	1.000	.845

Table E3. All variables - Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.865	74.438	74.438	17.865	74.438	74.438	4.317	17.988	17.988
2	1.155	4.812	79.250	1.155	4.812	79.250	3.897	16.236	34.225
3	.831	3.462	82.712	.831	3.462	82.712	3.276	13.648	47.873
4	.614	2.558	85.270	.614	2.558	85.270	3.271	13.628	61.500
5	.426	1.775	87.045	.426	1.775	87.045	3.169	13.206	74.706
6	.338	1.410	88.455	.338	1.410	88.455	1.927	8.027	82.734
7	.325	1.352	89.808	.325	1.352	89.808	1.698	7.074	89.808

Table E4. All variables - Rotated Component Matrix

	Component						
	1	2	3	4	5	6	7
INT1				.761			
INT2				.746			
INT3				.702			
ET1			.687				
ET2			.718				
ET3			.703				
CTAb1					.642		
CTAb2					.657		
CTAb3					.707		
CTAb4					.598		
CTInt1		.708					
CTInt2		.694					
CTInt3		.659					
CTInt4		.667					
CTBen1							.567
CTBen2							.569
CTBen3							.513
PEoU1	.805						
PEoU2	.738						
PEoU3	.759						
PU1						.593	
PU2						.583	
PU3	.509					.543	
PU4	.568						

At the next step EFA is realized for perceived ease of use and perceived usefulness, results are presented at Table E5, Table E6, Table E7, and Table E8.

Table E5. PEoU and PU - KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.927
Bartlett's Test of Sphericity	Approx. Chi-Square	2965.548
	df	21
	Sig.	.000

Table E6. PEoU and PU - Communalities

	Initial	Extraction
PEoU1	1.000	.916
PEoU2	1.000	.913
PEoU3	1.000	.910
PU1	1.000	.883
PU2	1.000	.884
PU3	1.000	.889
PU4	1.000	.840

Table E7. PEoU and PU - Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.845	83.497	83.497	5.845	83.497	83.497	3.233	46.179	46.179
2	.390	5.567	89.064	.390	5.567	89.064	3.002	42.885	89.064

Table E8. PEoU and PU - Rotated Component Matrix

	Component	
	1	2
PEoU1		.867
PEoU2	.548	.782
PEoU3	.504	.810
PU1	.829	
PU2	.836	
PU3	.805	
PU4	.693	.600

After deleting PU4, EFA is realized for all variables; results are presented at Table E9, Table E10, Table E11, and Table E12.

Table E9. All variables after deleting PU4 - KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.971
Bartlett's Test of Sphericity	Approx. Chi-Square	11030.780
	df	253
	Sig.	.000

Table E10. All variables after deleting PU4 - Communalities

	Initial	Extraction
INT1	1.000	.919
INT2	1.000	.930
INT3	1.000	.907
ET1	1.000	.912
ET2	1.000	.925
ET3	1.000	.928
CTAb1	1.000	.899
CTAb2	1.000	.901
CTAb3	1.000	.928
CTAb4	1.000	.840
CTInt1	1.000	.887
CTInt2	1.000	.896
CTInt3	1.000	.866
CTInt4	1.000	.857
CTBen1	1.000	.891
CTBen2	1.000	.907
CTBen3	1.000	.888
PEoU1	1.000	.917
PEoU2	1.000	.910
PEoU3	1.000	.920
PU1	1.000	.908
PU2	1.000	.892
PU3	1.000	.904

Table E11. All variables after deleting PU4 - Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	17.097	74.336	74.336	17.097	74.336	74.336	3.770	16.393	16.393
2	1.118	4.860	79.196	1.118	4.860	79.196	3.716	16.155	32.548
3	.823	3.579	82.775	.823	3.579	82.775	3.217	13.986	46.533
4	.611	2.658	85.434	.611	2.658	85.434	3.196	13.898	60.431
5	.423	1.840	87.273	.423	1.840	87.273	3.147	13.681	74.112
6	.338	1.469	88.742	.338	1.469	88.742	1.912	8.314	82.426
7	.322	1.401	90.143	.322	1.401	90.143	1.775	7.717	90.143

Table E12. All variables after deleting PU4 - Rotated Component Matrix

	Component						
	1	2	3	4	5	6	7
INT1			.761				
INT2			.747				
INT3			.703				
ET1				.690			
ET2				.719			
ET3				.706			
CTAb1					.643		
CTAb2					.656		
CTAb3					.713		
CTAb4					.602		
CTInt1	.710						
CTInt2	.697						
CTInt3	.653						
CTInt4	.664						
CTBen1							.576
CTBen2		.436					.586
CTBen3	.470						.531
PEoU1		.801					
PEoU2		.720					
PEoU3		.749					
PU1						.609	
PU2						.603	
PU3		.477				.551	

Keeping PU4 deleted, EFA is then realized for cognitive trust integrity, cognitive trust benevolence, perceived ease of use and perceived usefulness; results are presented at Table E13, Table E14, Table E15, and Table E16.

Table E13. CTIn, CTBen, PEoU and PU - KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.951
Bartlett's Test of Sphericity	Approx. Chi-Square	5691.827
	df	78
	Sig.	0.000

Table E14. CTIn, CTBen, PEoU and PU - Communalities

	Initial	Extraction
CTInt1	1.000	.892
CTInt2	1.000	.889
CTInt3	1.000	.872
CTInt4	1.000	.854
CTBen1	1.000	.901
CTBen2	1.000	.910
CTBen3	1.000	.887
PEoU1	1.000	.913
PEoU2	1.000	.909
PEoU3	1.000	.919
PU1	1.000	.894
PU2	1.000	.892
PU3	1.000	.895

Table E15. CTIn, CTBen, PEoU and PU - Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.892	76.092	76.092	9.892	76.092	76.092	3.849	29.606	29.606
2	.927	7.129	83.221	.927	7.129	83.221	3.042	23.397	53.002
3	.424	3.263	86.484	.424	3.263	86.484	2.576	19.814	72.816
4	.384	2.953	89.437	.384	2.953	89.437	2.161	16.621	89.437

Table E16. CTIn, CTBen, PEoU and PU - Rotated Component Matrix

	Component			
	1	2	3	4
CTInt1	.830			
CTInt2	.791			
CTInt3	.774			
CTInt4	.760			
CTBen1				.687
CTBen2				.671
CTBen3	.542			.642
PEoU1		.816		
PEoU2		.729		
PEoU3		.769		
PU1			.708	
PU2			.719	
PU3			.709	

EFA is lastly realized for cognitive trust integrity and cognitive trust benevolence; results are presented at Table E17, Table E18, Table E19, and Table E20.

Table E17. CTIn and CTBen - KMO

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.923
Bartlett's Test of Sphericity	Approx. Chi-Square	2753.972
	df	21
	Sig.	0.000

Table E18. CTIn and CTBen - Communalities

	Initial	Extraction
CTInt1	1.000	.889
CTInt2	1.000	.889
CTInt3	1.000	.871
CTInt4	1.000	.849
CTBen1	1.000	.890
CTBen2	1.000	.902
CTBen3	1.000	.878

Table E19. CTIn and CTBen - Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.721	81.723	81.723	5.721	81.723	81.723	3.306	47.232	47.232
2	.447	6.388	88.110	.447	6.388	88.110	2.861	40.878	88.110

Table E20. CTIn and CTBen - Rotated Component Matrix

	Component	
	1	2
CTInt1	.855	
CTInt2	.816	
CTInt3	.809	
CTInt4	.773	.501
CTBen1		.830
CTBen2		.853
CTBen3	.532	.772

APPENDIX F

CONFIRMATORY FACTOR ANALYSIS DETAILS

As Table F1 shows construct validity is assured by high standardized regression weights.

Table F1. Standardized Regression Weights: (All - Default model)

			Estimate
CTAb4	<---	CTAbility	.889
CTAb3	<---	CTAbility	.932
CTAb2	<---	CTAbility	.925
CTAb1	<---	CTAbility	.938
CTIn4	<---	CTIntegrity	.899
CTIn3	<---	CTIntegrity	.913
CTIn2	<---	CTIntegrity	.923
CTIn1	<---	CTIntegrity	.910
CTBen3	<---	CTBenevolence	.918
CTBen2	<---	CTBenevolence	.910
CTBen1	<---	CTBenevolence	.907
ET3	<---	ET	.937
ET2	<---	ET	.940
ET1	<---	ET	.940
PEoU3	<---	PEoU	.942
PEoU2	<---	PEoU	.946
PEoU1	<---	PEoU	.905
PU3	<---	PU	.920
PU2	<---	PU	.914
PU1	<---	PU	.912
INT3	<---	INT	.934
INT2	<---	INT	.949
INT1	<---	INT	.922

Discriminant validity is achieved by positive Fornell Lacker values, as presented at Table F2.

Table F2. Discriminant Validity

	AVE	Correlation		Correlation²	Fornell Lacker
Cognitive Trust Ability	.849	CTInt	.912	.832	.017
		CTBen	.833	.694	.155
		ET	.798	.637	.212
		PEoU	.811	.658	.191
		PU	.827	.684	.165
		INT	.878	.771	.078
Cognitive Trust Integrity	.830	CTBen	.907	.823	.008
		ET	.852	.726	.105
		PEoU	.787	.619	.211
		PU	.817	.667	.163
		INT	.834	.696	.135
Cognitive Trust Benevolence	.831	ET	.911	.830	.001
		PEoU	.841	.707	.124
		PU	.874	.764	.067
		INT	.802	.643	.188
Emotional Trust	.882	PEoU	.813	.661	.221
		PU	.886	.785	.097
		INT	.790	.624	.258
Perceived Ease of Use	.867	PU	.913	.834	.034
		INT	.759	.576	.291
Perceived Usefulness	.838	INT	.803	.645	.193

Multisample CFA scalar invariance details are presented at Table F3.

Table F3. Scalar Invariance

	Est.	S.E.	C.R.	P	Label	Difference	Est.	S.E.	C.R.	P	Label
CTAb4	5.105	.123	41.369	***	i1_1	0.645	5.750	.103	56.090	***	i1_2
CTAb3	5.248	.117	44.858	***	i2_1	0.550	5.798	.102	56.783	***	i2_2
CTAb2	5.248	.116	45.432	***	i3_1	0.491	5.739	.106	54.184	***	i3_2
CTAb1	5.196	.121	42.981	***	i4_1	0.634	5.830	.103	56.616	***	i4_2
CTIn4	4.915	.128	38.268	***	i5_1	0.755	5.670	.105	53.990	***	i5_2
CTIn3	5.007	.118	42.366	***	i6_1	0.567	5.574	.104	53.606	***	i6_2
CTIn2	5.000	.124	40.426	***	i7_1	0.580	5.580	.115	48.462	***	i7_2
CTIn1	5.046	.125	40.307	***	i8_1	0.555	5.601	.108	51.910	***	i8_2
CTBen3	4.967	.132	37.569	***	i9_1	0.650	5.617	.109	51.473	***	i9_2
CTBen2	4.993	.125	39.873	***	i10_1	0.725	5.718	.103	55.718	***	i10_2
CTBen1	5.000	.136	36.698	***	i11_1	0.601	5.601	.111	50.685	***	i11_2
ET3	5.046	.126	40.088	***	i12_1	0.853	5.899	.099	59.524	***	i12_2
ET2	5.124	.121	42.230	***	i13_1	0.780	5.904	.099	59.475	***	i13_2
ET1	5.052	.123	40.988	***	i14_1	0.842	5.894	.100	58.894	***	i14_2
PEoU3	5.379	.119	45.034	***	i15_1	0.515	5.894	.106	55.807	***	i15_2
PEoU2	5.359	.117	45.760	***	i16_1	0.487	5.846	.106	55.308	***	i16_2
PEoU1	5.431	.110	49.381	***	i17_1	0.436	5.867	.103	56.740	***	i17_2
PU3	5.229	.121	43.196	***	i18_1	0.659	5.888	.103	57.331	***	i18_2
PU2	5.327	.118	45.168	***	i19_1	0.599	5.926	.101	58.625	***	i19_2
PU1	5.196	.122	42.730	***	i20_1	0.597	5.793	.109	53.051	***	i20_2
INT3	5.216	.127	41.149	***	i21_1	0.539	5.755	.115	50.043	***	i21_2
INT2	5.209	.122	42.641	***	i22_1	0.530	5.739	.111	51.747	***	i22_2
INT1	5.190	.127	40.746	***	i23_1	0.624	5.814	.103	56.618	***	i23_2

APPENDIX G

STATISTICAL DETAILS - STUDY 1

Recommendation type post hoc analysis shows a significant difference between Basic and Upsell recommendation types, as demonstrated at Table G1.

Table G1. Post Hoc Analysis for Recommendation Type

(I) Recommendation Type		Mean Difference (I-J)	Std. Error	Sig.
Basic	Upsell	.611	.216	.047
	Cross sell	.099	.225	.979
	Design	.101	.217	.975
Upsell	Basic	-.611	.216	.047
	Cross sell	-.512	.227	.168
	Design	-.510	.219	.146
Cross sell	Basic	-.099	.225	.979
	Upsell	.512	.227	.168
	Design	.002	.229	1.000
Design	Basic	-.101	.217	.975
	Upsell	.510	.219	.146
	Cross sell	-.002	.229	1.000

Trust propensity and need for uniqueness are studied as covariates. For trust propensity Levene's test delivered not significant results, as presented at Table G2. Next step analysis showed significant impact of recommendation source and recommendation type, but not for the interaction. Results are provided at Table G3.

Table G2. Trust Propensity - Equality of Error Variances

F	df1	df2	Sig.
.407	7	333	.898

Table G3. Trust Propensity - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Trust Propensity	107.043	1	107.043	60.262	.000
Recommendation Type	14.199	3	4.733	2.664	.048
Recommendation Source	15.271	1	15.271	8.597	.004
Recommendation Type * Recommendation Source	1.081	3	.360	.203	.894

For need for uniqueness, Levene's test delivered not significant results, as presented at Table G4. Next step analysis showed significant impact of recommendation source, but not for recommendation type and for the interaction. Results are provided at Table G5.

Table G4. Need For Uniqueness - Equality of Error Variances

F	df1	df2	Sig.
.982	7	333	.444

Table G5. Need For Uniqueness - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Need for Uniqueness	187.494	1	187.494	122.228	.000
Recommendation Type	8.330	3	2.777	1.810	.145
Recommendation Source	6.680	1	6.680	4.355	.038
Recommendation Type * Recommendation Source	1.340	3	.447	.291	.832

APPENDIX H

NORMALITY PLOTS - STUDY 2

Data normality is checked visually at Figure H1.

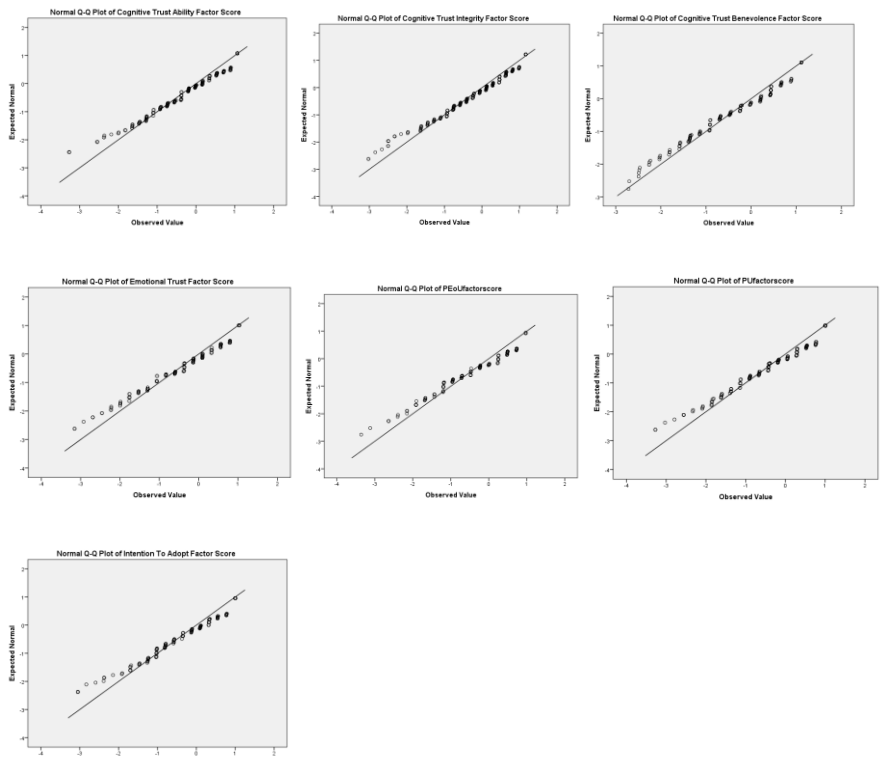


Figure H1. Q/Q plots

APPENDIX I

STATISTICAL DETAILS - STUDY 2

Data normality analysis is presented at Table I1.

Table I1. Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CTAbility	.142	341	.000	.899	341	.000
CT Integrity	.122	341	.000	.921	341	.000
CT Benevolence	.134	341	.000	.907	341	.000
Emotional Trust	.161	341	.000	.887	341	.000
Intention to Adopt	.179	341	.000	.878	341	.000

For analyzing the case of recommendation type, it is kept as the fixed factor, whereby emotional trust and cognitive trust dimensions are taken as the dependent variables. Results are presented at Table I2 and Table I3.

Table I2. ET and CT as dependent variables - Test of Homogeneity

	Levene Statistic	df1	df2	Sig.
Emotional Trust	.420	3	337	.739
Cognitive Trust Ability	.373	3	337	.772
Cognitive Trust Integrity	.120	3	337	.948
Cognitive Trust Benevolence	.579	3	337	.629

Table I3. ET and CT as dependent variables - Anova

		Sum of Squares	df	Mean Square	F	Sig.
Emotional Trust	Between Groups	9.920	3	3.307	1.615	.186
	Within Groups	690.157	337	2.048		
	Total	700.078	340			
Cognitive Trust Ability	Between Groups	11.292	3	3.764	1.986	.116
	Within Groups	638.834	337	1.896		
	Total	650.126	340			
Cognitive Trust Integrity	Between Groups	8.847	3	2.949	1.442	.230
	Within Groups	689.185	337	2.045		
	Total	698.032	340			
Cognitive Trust Benevolence	Between Groups	8.774	3	2.925	1.332	.264
	Within Groups	739.910	337	2.196		
	Total	748.684	340			

Then, recommendation source and recommendation type are kept as the fixed factors, whereby emotional trust is taken as the dependent variable. Results are presented at Table I4 and Table I5.

Table I4. ET as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
1.226	7	333	.287

Table I5. ET as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Source	57.144	1	57.144	30.241	.000
Recommendation Type	9.940	3	3.313	1.753	.156
Recommendation Source * Recommendation Type	2.993	3	.998	.528	.663

Similarly, recommendation source and recommendation type are kept as the fixed factors, whereby first cognitive trust ability, then cognitive trust integrity, and lastly cognitive trust benevolence are taken as the dependent variable. Results are presented at Table I6, Table I7, Table I8, Table I9, Table I10, and Table I11.

Table I6. CTAb as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
1.202	7	333	.301

Table I7. CTAb as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Source	28.066	1	28.066	15.355	.000
Recommendation Type	11.052	3	3.684	2.015	.112
Recommendation Source * Recommendation Type	1.744	3	.581	.318	.812

Table I8. CTIn as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
.894	7	333	.511

Table I9. CTIn as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Source	31.477	1	31.477	15.997	.000
Recommendation Type	9.204	3	3.068	1.559	.199
Recommendation Source * Recommendation Type	1.636	3	.545	.277	.842

Table I10. CTBen as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
1.061	7	333	.389

Table I11. CTBen as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Source	34.737	1	34.737	16.550	.000
Recommendation Type	9.362	3	3.121	1.487	.218
Recommendation Source * Recommendation Type	4.144	3	1.381	.658	.578

APPENDIX J

NORMALITY PLOTS - STUDY 3

Data normality is checked visually at Figure J1.

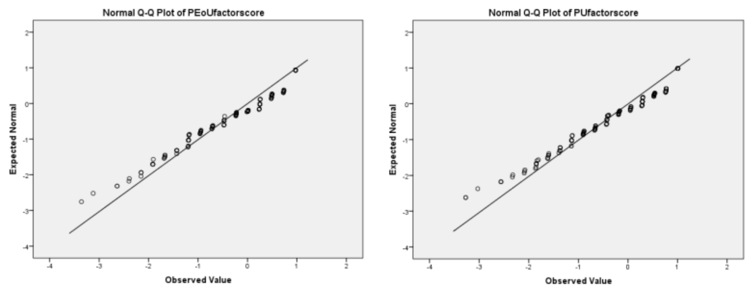


Figure J1. Q/Q plots

APPENDIX K

STATISTICAL DETAILS - STUDY 3

Data normality analysis is presented at Table K1.

Table K1. Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Perceived Ease of Use	.183	341	.000	.868	341	.000
Perceived Usefulness	.165	341	.000	.881	341	.000
Intention to Adopt	.179	341	.000	.878	341	.000

Recommendation source and recommendation type are kept as the fixed factors, whereby perceived ease of use as is taken as the dependent variable. Results are presented at Table K2 and Table K3.

Table K2. PEoU as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
1.170	7	333	.319

Table K3. PEoU as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Type	13.190	3	4.397	2.361	.071
Recommendation Source	19.471	1	19.471	10.455	.001
Recommendation Type * Recommendation Source	.750	3	.250	.134	.940

Then, recommendation source and recommendation type are kept as the fixed factors, whereby perceived usefulness is taken as the dependent variable. Results are presented at Table K4 and Table K5. Lastly, recommendation type is kept as the fixed factor; whereby perceived ease of use and perceived usefulness are taken as the dependent variables. Results are presented at Table K6 and Table K7. As perceived usefulness delivered significant difference at these two studies, a further post hoc analysis is run for perceived usefulness and presented at Table K8.

Table K4. PU as dependent variable - Equality of Error Variances

F	df1	df2	Sig.
1.236	7	333	.282

Table K5. PU as dependent variable - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Recommendation Type	15.841	3	5.280	2.843	.038
Recommendation Source	31.550	1	31.550	16.985	.000
Recommendation Type * Recommendation Source	3.320	3	1.107	.596	.618

Table K6. PEoU and PU as dependent variables - Test of Homogeneity

	Levene Statistic	df1	df2	Sig.
Perceived Ease of Use	1.519	3	337	.209
Perceived Usefulness	.537	3	337	.657

Table K7. PEoU and PU as dependent variables - ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Perceived Ease of Use	Between Groups	13.349	3	4.450	2.342	.073
	Within Groups	640.262	337	1.900		
	Total	653.612	340			
Perceived Usefulness	Between Groups	15.844	3	5.281	2.721	.044
	Within Groups	654.113	337	1.941		
	Total	669.957	340			

Table K8. PU - Post Hoc Analysis

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.
Perceived Usefulness	Basic	Upsell	.450	.208	.199
		Cross sell	-.130	.217	.948
		Design	.052	.209	.996
	Upsell	Basic	-.450	.208	.199
		Cross sell	-.580	.219	.073
		Design	-.397	.211	.318
	Cross sell	Basic	.130	.217	.948
		Upsell	.580	.219	.073
		Design	.183	.220	.876
	Design	Basic	-.052	.209	.996
		Upsell	.397	.211	.318
		Cross sell	-.183	.220	.876

APPENDIX L

COMPARATIVE MODEL FIGURE - STUDY 4

A comparative model is presented at Figure L1.

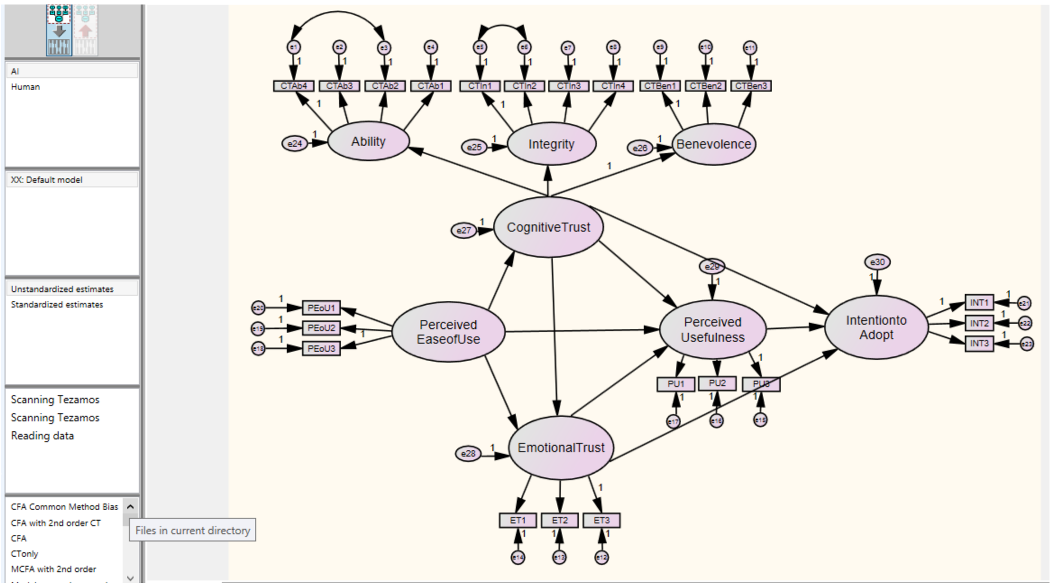


Figure L1. Comparative model

APPENDIX M

COMPARATIVE MODEL DETAILS - STUDY 4

The comparative model delivers a good fit as presented at Table M1, but fails in standardized regression weights, where a Heywood case is observed for AI at the path between cognitive trust and intention to adopt as demonstrated at Table M2.

Table M1. Fit Indices for Comparative Model

Chi-square (χ^2)	
Chi-square	= 1062.064
Degrees of freedom	= 432
Probability level	= .000
Absolute Fit Indices	
RMSEA	= .066
SRMR	= .049
Normed χ^2	= 2.458
Incremental Fit Indices	
Comparative Fit Index (CFI)	= .944
Normed Fit Index (NFI)	= .909
Relative Fit Index (RFI)	= .894

Table M2. Standardized Regression Weights: (AI - Default model)

			Estimate	P
CT	<---	PEoU	0.798	***
ET	<---	PEoU	0.224	0.005
ET	<---	CT	0.718	***
PU	<---	PEoU	0.626	***
PU	<---	CT	0.185	0.046
PU	<---	ET	0.218	0.017
INT	<---	PU	0.229	***
INT	<---	CT	1.140	0.093
INT	<---	ET	-0.522	***

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