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Predictive shift of Customer Satisfaction measurement: How explainable AI impacts the final perceived credibility under the influence of users' concerns.

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List of abbreviations

Abbreviation	**Definition**
PA	Predictive Analytics
XAI	Explainable AI
CX	Customer Experience

Introduction

Artificial Intelligence is significantly revolutionizing several business practices, delivering new opportunities and tools to enhance marketing activities. By leveraging massive data collection and processing capabilities, AI models have been trained and improved with the goal of foreseeing certain phenomena, endowing companies with predictive insights that nowadays resemble a key competitive advantage. As a result, predictive artificial intelligence will increasingly influence performance measurement and marketing KPIs, setting the tone for a potential technological transition. Specifically, qualitative metrics are the least impacted by this shift due to their nature, and for this reason, require further academic investigation.

This experimental study will examine how predictive AI might disrupt Customer Satisfaction measurement, focusing on how explainable artificial intelligence could help facilitate this transition while evaluating the influence of individuals' psychological concerns. Going into detail, our research investigates how explainable AI affects individuals' perceived credibility of artificial intelligence employed to predict customer satisfaction, assuming to replace traditional post-purchase surveys. Previous research explores AI and machine learning technical efficiency in predicting customer sentiment, yet further study is needed to assess how explainable AI can impact users' reliance on such solutions. This experimental research contributes to examining the correlation between AI *explainability* and users' perceived credibility when mediated by the perception of intrusiveness, showcasing a positive and significant effect between the two main variables.

The first chapter will examine how big data and artificial intelligence disrupt the marketing domain, highlighting the most crucial benefits and enhancements these innovations deliver for business purposes. Relevant trends and stats will be provided to showcase this phenomenon's importance. Afterward, the focus will shift to the impact that these technologies are having on performance measurement practices, and on Customer Satisfaction in particular: thereafter, the predictive transition leveraged on AI's outstanding capabilities will be introduced while giving resonance to the potential threats and concerns that consumers face when interacting with artificial intelligence. Lastly, the concept of explainable AI will be introduced as a key enabler for the adoption and acceptance of these technologies from the user side.

The second chapter will provide an extensive review of the relevant academic literature about our research topic, exploring in depth the relationship between the variables of the conceptual model, which will be presented at the end of the section. After assessing the requirements for reliance on and acceptance of AI solutions, the importance of users' trust and understanding of such technologies is investigated in relation to their credibility. Thereafter, the role of explainable AI inside this context will be analysed in depth, focusing on its tangible benefits for AI acceptance. Subsequently, the study will highlight how ethics and safety risks can play a crucial role in our framework, defining perceived intrusiveness as a mediating variable inside our main relationship.

In the last chapter, after presenting the methodology and procedure used to collect data to test our research hypotheses, data will be analysed assessing the results of each hypothesis tested in the experimental study, checking for statistical significance and validity of the relationships between factors. Lastly, we deliver the study's theoretical contribution and the managerial implications of the findings, also discussing the study's limitations and potential future directions for research about the subject.

Chapter 1 – Performance measurement evolution and the AI-based predictive shift: the role of explainable AI and users' psychology

1.1 Mar-Tech evolution: a data-driven ecosystem

Marketing practices and the related tracking of performance levels have been facing an exponential evolution in recent decades, as both the digital and technological transition forced organizations to rethink and optimize the metrics employed. This need for adaptation is fostered by the fast-paced environment in which companies are called to operate, dealing with huge amounts of data and complex patterns to be tracked to monitor performance levels. According to McKinsey (2018), Mar-Tech's widespread has been empowering companies to better understand their customer base (increasing engagement and conversion rates) and enhancing the final value created. This technological evolution has been so impactful in this field that even the relevance of traditional marketing bedrock, such as the 4 P's, started to be put under question (Rust, 2020).

This shift is fostered by the establishment of a data-driven eco-system and the increased relevance of AI and machine learning, which contribute to a quality increase for companies' relevant indicators and performance metrics (Saura, 2021). According to a report by PWC, to be relevant, data that feed performance indicators need to have historical tracking and to be comparable over time: only in this way, these metrics will succeed in adapting to market changes and variable strategic needs. At the same time, these requirements imply the necessity of constant updates to the system and enough agility to deal with impressive amounts of data (Ameen et al., 2020).

For instance, Big Data empowers marketers to gain predictive insights based on extensive information containers, which provide competitive and strategic advantages (Gnizy, 2020). Nowadays, data is coming from several sources (such as social media, the Internet of Things, or transaction processing systems), which allow organizations to store and analyse massive amounts of information, useful to improve management decisions (McKinsey, 2011). This wide range of data comprehends information on customer interactions, transactions, and profiles, but also widely accessible third-party data sets that cover customer attitudes, purchase behaviours, and preferences.

Additionally, AI-powered marketing means are recognized to augment the customer experience, value creation process, and generate sales (Barnes, 2020). To put it in numbers, the AI market size worldwide is expected to grow almost twentyfold by 2030, reaching more than 1.800 billion dollars (Statista, 2023). Consequently, AI adoption inside organizations connects significantly to customer service analytics, a growing phenomenon 2.5 times higher in 2022 compared to 2017 (McKinsey, 2022), disrupting the way companies interact and obtain feedback from their audiences. At the same time, despite 84% of business executives considering AI a key instrument to drive growth, 76% of them still struggle to scale this technology inside their processes (Accenture), highlighting how complex the adaptation to these new technologies can be.

1.2 AI influence on marketing domain

It is beyond doubt how in recent years AI has been affecting many business fields, influencing companies' practices, structure, and internal operations. Data has become the primary driver of information and insights for companies: As a result, AI's importance inside this landscape has been growing exponentially, as it allows to exploit the full potential of data stored. Top-line-oriented functions such as marketing and sales, are recognized to have the highest potential value impact from AI's usage (McKinsey, 2018).

The capabilities and tasks that AI can perform are incredibly broad, however, its tangible impact on organizations' practices requires clarity. According to Harvard Business Review (2021), two main types of Marketing AI can be outlined, based on their level of complexity and the outcomes delivered: task automation, which handles simple and repetitive tasks with a low level of intelligence required (e.g. simple chatbots or basic interaction intelligence), and machine learning, that works with big amounts of data to deliver predictions and help decisions (e.g. recommendation engines and CRM).

Overall, automation has conveyed remarkable advantages to marketers, such as time-saving and cost-reducing related to activities such as content creation and email campaigns (Griffith College, 2023). Specifically, chatbots are disrupting customer experience in many sectors, as this technology allows to assist and solve consumers' needs instantly, reducing companies' effort to deal with requests and complaints from their audience (Forbes, 2019). Additionally, task automation and machine learning can be expanded if integrated into broader platforms: integrated AI applications are more complicated to set up but deliver the highest benefits and create more value. In this way, AI can be embedded into external systems and is no longer an isolated tool.

Going into detail, AI deployment for marketing is exponentially increasing and the three main marketing areas taking advantage of this technology are content personalization, predictive analytics for customer insights, and targeting decisions (American Marketing Association, 2019). Specifically, personalization of contents, one of the main activities conducted by marketers currently, heavily leverages AI's ability to deal with enormous amounts of consumer data: key insights such as time spent on a page, click rates, and real-time predictions are being extracted, enabling companies to fasten and optimize value creation. As a matter of fact, personalization is crucial nowadays to make consumers feel understood and connected to a company: 63% of customers perceive personalization as required and 45% of them see it as a driver of purchasing intention (Marketing AI Institute, 2022).

Inside this landscape, we are called to take into consideration Generative AI, one of the latest and most trending AI frontiers (e.g., ChatGPT), which will revolutionize several industries in the near future: differently from the previously mentioned technologies, Generative AI is a type of intelligence able to autonomously create contents (such as images, videos or audios). As a result, it can be employed to produce marketing campaigns, by personalizing experiences, content, and product recommendations autonomously, leveraging on huge datasets (BCG, 2023): In turn, Generative AI implies growth of labour productivity, acceleration of R&D and creation of new business models.

As a result, it seems clear how Artificial Intelligence's spread is facilitated by customers' need for optimized, fast-paced, and tailored experiences: algorithms thus resemble a suitable tool for the complex and technological environment in which we live nowadays, both as individuals and as consumers. Its recent evolution, which points towards the ability to be highly reactive and predictive, but also to produce solutions by itself to those who use it, is disrupting several practices, particularly marketing activities. Tasks that were previously carried through human labour or ideas coming from human thinking can now be handled by different types of artificial intelligence, which are revolutionizing businesses at their core. Nowadays, data has become an incredibly valuable asset, and its analysis is key to obtaining insights, boosting growth, and building strategies. The choice of if and how to use these technologies remains upon organizations' operational needs and outcomes to be reached.

1.3 Performance measurement and customer experience evolution

All these enhancements are not only changing the way companies interact with users but also how they generate insights and measure performance. The collection and analysis of data have already altered relevant business practices: Companies' strategic decisions will inevitably be more and more dependent on Artificial Intelligence, the leading field of this sector. Therefore, performance measurements in the future will be increasingly affected by this transition: KPIs will therefore necessitate being highly adaptive, to both capture insightful information and be up to date.

As a matter of fact, performance indicators driven by big data analytics have become a fast-growing trend in the last few years, as these tools have proven to increase predictive performance management (Kamble & Gunasekaran, 2020). Given the fast pace at which markets change, leveraging AI capabilities (especially when a consistent volume of data is involved) allows to speed up the time to obtain feedback from a company's marketing activities, and as a result, the overall decision-making process is boosted (Stone et al., 2020).

The ability to mix traditional and 4.0 KPIs allows companies to discover hidden patterns and unexplored relationships that might be crucial for a company's business purposes (Sishi & Telukdarie, 2021): According to the authors, this blended approach requires a strong commitment toward an optimized KPIs model, built on digital technologies and artificial intelligence. Despite this change being quite challenging for many organizations, it allows to obtain a stronger predictive capacity and more adaptability to markets in continuous motion. Indeed, AI empowers marketers to establish a customer-centric approach, understanding better the needs and behaviours of their target audience, and deploying effective data analysis techniques (Vlačić et al., 2021).

Without any doubt, KPI's evolution can already be observed in the digital sphere of marketing, as modern metrics are proven to increase the effectiveness of marketing practices and to ensure an optimal allocation of budgets (Ghahremani-Nahr & Nozari, 2021). Determining the effectiveness of certain marketing activities inside the digital domain is a very challenging task for marketers and requires the implementation of up-to-date tools. Web analytics (both quantitative and qualitative) for example are being used first to figure out consumers' behaviour and then to analyse more in-depth trends and marketing activities' performance (Saura et al., 2017): These sources can then be helpful for companies to define effective long-term marketing strategies and reach a competitive advantage over competitors.

As a result, KPIs nowadays are starting to point towards a more predictive dimension with a higher degree of reliance on AI's predictive ability. Specifically, machine learning, a prevalent branch of Artificial Intelligence, is able to find patterns and produce estimates based on historical data: this technology has been widely employed for recommendation engines, which use past consumption behavior data to develop relevant suggestions (IBM). Mainstream websites and platforms (such as Amazon, Netflix, or YouTube) already use the previously mentioned techniques in order to gain a competitive advantage over competitors, understand in depth of their customer base, and convey the highest value possible. As a result, these data journeys in which customers take part are perceived as inevitable, being this exchange beneficial for both sides: companies collect data to increase the performance and profitability of their marketing activities, while users receive a more tailored and adequate consumption experience. Specifically, marketing and sales benefit from predictive analytics as decision-making is optimized and overall risk faced by companies is reduced: As a result, this evolution implies a shift towards a more proactive (rather than reactive) approach when interfacing with their target audience (IBM).

1.4 Customer Satisfaction measurement: framework and future directions

Customer Satisfaction, a leading indicator of consumer purchase intentions and loyalty (Farris et al., 2010), is expected to face several changes in the future: the metric in question provides the extent to which a company's product or service meets customers' expectations, investigating the perceived quality of the experience. Leading satisfaction indicator CSAT measures through surveys consumers' fulfilment about specific aspects of their consumption experience, answering with a precise percentage that ranges from 0 to 100: a number above 80% denotes a satisfied customer (CFI, 2023). Specifically, customer satisfaction is measured according to four key dimensions, which provide a complete understanding of the extent to which a customer is satisfied: overall satisfaction (perception of quality and happiness of their choice), loyalty (probability of repeat purchase), attribute satisfaction (quality of specific characteristics), and intent to repurchase (a measure of brand loyalty) (SalesForce, 2023).

Additionally, customer satisfaction measurement is completed by two additional methods, which provide a complete overview of the consumption experience. The first one, NPS (Net Promoter Score), divides customers into three categories, promoters, passives, and detractors: It is calculated as the subtraction between the percentage of the first and last category and provides the probability with which consumers will promote the brand. Being recognized by Bain & Company as a leading indicator of a company's future growth, it allows tracking customer sentiment over time. The second method, CES (Customer Effort Score), investigates customers' perceived effort to solve an encountered issue during the experience, and its score allows to optimize resolution times and service quality.

All these satisfaction metrics rely on traditional data gathering, such as surveys launched and filled right after the consumption experience. However, as technology and analytics increase their reach, CSAT and NPS are starting to be questioned regarding their completeness and accountability (Flores-Kilfoyle, 2019), as AI is entering this field.

1.5 The predictive transition: technologies and their impact

Predictive analytics (PA), the main character of the following research, has seen an exponential rise in recent years: its global market generated 13.5 billion dollars in 2022, and is expected to grow exponentially in the future, reaching 41.52 billion by 2028 (Statista, 2023), with IT giants such as Google, Oracle, Microsoft, and IBM leading the way for this technological transition. PA is a subset of advanced analytics that uses historical data along with statistical modeling, data mining, and machine learning to generate predictions about future outcomes, but also to detect threats and opportunities (IBM). Specifically, predictive models are crucial to gaining key insights, such as binary distinctions on a targeted event (Classification models) or providing a numerical prediction on a given phenomenon (Regression models) (SAS).

As explained before, customer experience (CX) has been historically based on post-purchase questionnaires which require time and effort to be collected and then analysed. According to a survey by McKinsey (2021), this process is perceived by professionals to be quite inefficient at measuring customer experience's dimensions in time, lacking proactivity. Furthermore, the survey highlights how post-hoc measurement of CX is perceived nowadays to provide a limited evaluation of value creation, being a back-word-looking instrument with shifty interpretations. As a result, it seems evident how post-purchase analysis of customers' feedback (through surveys) and predictive analytics are called to coexist nowadays and to be integrated by companies to exploit the full potential of customer experience.

These techniques empower using the past to have an anticipated view of the future: as a result, the shift from reactivity to proactivity is already underway, as predictive analytics allow to obtain real-time feedback or predictions on users' attitudes towards consumption (Forbes, 2019): this feature is crucial for streaming platforms (such as Netflix or Spotify), which can adjust their recommendations right after receiving input. Predictive analytics not only is disrupting marketing activities of streaming services but also several operations of relevant business fields, such as healthcare, manufacturing, real estate, and more (Bhatt, 2021).

The relevance and connection of predictive analytics to performance measurement is an undisputed phenomenon: according to Schrage (2018), traditional KPIs – that shaped the 21st century's performance measurement - are not appropriate to the way value is generated and measured nowadays: reversing the original perspective, original KPIs should become inputs to train machine learning algorithms rather than mere outputs to track results. Therefore, data enters a looping process in which responses coming from post-purchase questionnaires provide valuable insights to instantly feed predictive analytics and gather projections useful to drive future decisions (IBM, 2016).

As a result, the information provided by customers becomes crucial in order to maximize the exchange and foster positive financial outcomes. By doing so, companies can save time by accelerating the understanding of their customer base, while providing them with smoother solutions and timely adjustments. Tangible benefits connected to the use of predictive analytics are for example more accurate financial predictions, the ability to predict customer retention and churn rates, or having analytical customer relationship management (Mishra & Silakari, 2012). Indeed, data analytics are a critical instrument to pursue both business (from the company's side) and personal (from the customer's side) goals (Sweenor, 2022): By taking advantage of these tools, companies can increase returns of marketing activities, while customers will benefit by receiving a more accurate and coherent value proposition in the future. Given the incontestable advantages that these technologies are bringing, what type of obstacles their adoption and acceptance are called to face, and what could hinder them from disrupting traditional measurement techniques?

1.6 AI-user interaction: psychological concerns

Within this context, a crucial role is inevitably played by consumers (end users of the value creation process) and their psychological relationship with the aforementioned innovations. Artificial intelligence not only changes our daily lives but will increasingly facilitate obtaining and exploiting information about customers for business purposes. As a result, users' attitudes and perceptions become a key dimension to analyse to assess the efficiency of the transition towards a predictive and intelligent measurement of performance, such as their overall satisfaction with the service or product consumed. According to Statista (2019), 53% of responding consumers believe that Artificial intelligence would disrupt how they interact with companies, while 56% believe that AI can enhance their experience; on the other hand, only 1 respondent out of 3 perceives transparency on how it is used and is able to give a concrete example of this technology.

As theorized by Vargo & Lush (2008) in their renowned *Service Dominant Logic*, the creation of value can be seen as a shared process that involves simultaneously different actors (service provider and beneficiary) inside a networked and interactive environment. Given the relevance of AI to the exchange between companies and customers, it seems clear how one initial barrier to be faced to consolidate this shift is users' resistance and lack of knowledge of the considered technologies. Thus, further understanding of the psychological relationship between humans and this ground-breaking form of intelligence is required to break down its potential inside the performance measurement domain.

According to CDP (2022), which surveyed more than 2,500 people, more than 40% of respondents are open to AI's impact on customer experience for advertising and customer service, while approximately 20% of them show a negative attitude towards it. Furthermore, the survey highlights how users who take advantage of this source of intelligence daily are more prone to manifest a positive impact on customer experience. At the same time, inevitable privacy and ethical concerns come out when people interact with artificial intelligence: around

80% of respondents to the survey consider AI a potential threat to their online privacy. As a result, when building their performance measurement approach, companies are called to take into account people's need for transparency and a clear understanding of how personal data is used; by doing so, data practices might be perceived as more beneficial and adequate from their side.

Furthermore, among US adults, the percentage of people concerned about the influence of AI on everyday life is significantly higher (37%) than the ones excited about it (18%), mainly due to fears of losing jobs, excessive power, risks of misusing and lack of human connection (Pew Research Center, 2022). This study provides a very interesting additional insight for our research purposes, useful for the following evaluations: 75% of respondents are significantly concerned about Artificial Intelligence's usage to make important decisions or get to know people's thoughts or behaviours. Additionally, AI algorithms exploited for business purposes might be responsible for biased decision-making, by providing misleading and unreliable takeaways (Jobin et al., 2019). Therefore, companies are called to have structured knowledge about how data is generated, the sources used to make predictions, and the origin of potential decisional bias. In turn, end users look for awareness of data practices concerning their personal sphere.

As AI applications grow relentlessly, intrusiveness and privacy concerns perceived by users are inevitable side effects: In order to function, large-scale personal data is frequently used by AI systems to learn and make predictions, which raises questions concerning the gathering, use, and archiving of such data. Large amounts of data are frequently used by AI systems to train their algorithms and boost performance. This information can include sensitive information such as names, residences, and financial data. Concerns about how data is utilized and who has access to it can arise from its collection and processing: potential risks to be faced can be data breaches (which can threaten personal safety and privacy), nudging (analytics' ability to invasively influence decisions), or secondary use (usage of personal data for unintended purposes) (Deloitte).

Stats confirm this psychological tendency: 81% of users consider personal data protection as a barrier to implementing AI, while 68% show a lack of trust and understanding of AI capabilities (Dentons, 2022). Additionally, according to McKinsey (2020), consumers place importance on what type and with whom they are sharing personal data, being more open to disclose when it is necessary and beneficial to the exchange with the company: healthcare and financial services (both involving sensitive data) are being perceived as the most trustworthy when it comes to data privacy, showing how the perceptions on data safety depend on the purpose and nature of service. Despite AI adoption being on an exponential rise, privacy and ethical aspects resemble a crucial issue to be addressed. The attention to privacy concerns and the transparency on data processing determine the overall quality of the exchange, but also consumers' willingness to disclose personal information. As a result, predictive AI settlement inside customer experience measurement must deal with several psychological and behavioural barriers to maximize its effectiveness: being a two-way exchange (in which users grant personal data that end up feeding the algorithms), the relationship between the technology and the individual plays a key role inside this context.

1.7 The role of explainable AI

Given the remarkable influence that AI applications are having on our everyday lives and the related concerns about personal privacy and security, countermeasures are needed to mitigate these barriers and facilitate the building of trust in the technology. As a result, Explainable AI (XAI), a set of procedures and techniques that enable human users to understand and have confidence in the outcomes and outputs generated by machine learning algorithms (IBM), has become an emerging field that aims at enhancing transparency and *explainability* of AI and machine learning algorithms. Given the black-box nature of AI systems, XAI's aim is to examine and comprehend the processes and models employed to make specific decisions, providing answers on how the model generated a prediction, whether it succeeded or failed, and how it could be improved it in the future (Forbes, 2019).

As AI engines increase in complexity, reaching appropriate solutions to convey information and explanations about the model has become a very challenging objective, being companies called to develop efficient tools that meet the needs of customers, employees, and regulators (McKinsey, 2022). Explainable AI is therefore destined to become a crucial requirement for all companies that aim to implement artificial intelligence systems to gain valuable insights and predictions for business purposes. Yet, it is widely debated how to choose, implement, and utilize those explanations, as *explainability* requirements are highly dependent on the context and the target to which information is displayed (Carnegie Mellon University, 2022).

Having the demand for transparency in the decision-making processes operated by AI models increased tremendously, with numerous businesses integrating AI and advanced analytics into business processes, we believe XAI holds immense potential for future implications. Considering how confidence in AI solutions enables their deployment, it is reasonable to assume that XAI can become an enabling component to foster the transition to innovative solutions, such as the prediction of customer sentiment through artificial intelligence models.

Undoubtedly, AI-based techniques have started being integrated with traditional measurement tools for customer experience, but questions arise about whether predictive AI will be able to sweep past measurement standards, becoming a unique source of truth. Focusing specifically on customer satisfaction measurement, the study will investigate whether predictive AI is perceived as reliable compared to traditional surveys and whether explainable AI can play a crucial role in the acceptance of this shift: therefore, XAI's role will be analysed in depth inside the following chapter, highlighting its pivotal role for this potential technological shift. In conclusion, despite the transition from reactivity to proactivity being perceived as inevitable, it requires in-depth and contextual analysis to understand its feasibility and final effectiveness: for this reason, the chapter two will review relevant literature concerning the topic, focusing on individuals' psychological concerns and their need for clarity and understanding related to predictive artificial intelligence. As a result, after exploring the theoretical relationship between the variables, our final research framework will be presented.

Chapter 2 – Literature Review

2.1 The relationship between explainable AI and credibility

After having introduced all the enhancements brought by artificial intelligence inside the marketing domain, and the connected transition towards a predictive dimension of performance measurement, in this chapter, we will dive deep into the relationship between the credibility and acceptance of an AI solution and its level of understanding and *explainability* from the user side. To prove the feasibility of the shift to predictive measurement of customer satisfaction (based on predictive analytics and AI) we will first go through relevant literature about the tangible effectiveness of these technologies while exploring attitudinal dimensions that highlight how consumers' psychology plays a crucial role inside the interaction. Users' perception of intrusiveness and the psychological concerns related to the interaction with the technology will be investigated as mediators of the relationship.

Broad academic research can be encountered about the benefits deriving from the implementation of AI and analytics to measure customer experience (CX), yet further research is needed to explore the potential replacement of traditional measurement techniques by predictive AI, and what would eventually drive it. Recent achievements in machine learning have fostered AI applications, bringing substantial advantages to different types of organizational and marketing practices. Nevertheless, a significant portion of these systems lack the capability to illustrate their independent decisions and actions to human users. Since we expect that an appropriate level of *explainability* positively influences the perceived credibility of the AI solution, we developed the first hypothesis:

H1) *An explainable implementation (explicit) of predictive AI to measure customer satisfaction influences more positively its perceived credibility compared to an unexplainable one (implicit).*

2.1.1 AI practical advantages for CX measurement: technical credibility

Without a doubt, modern analytics offer several benefits to companies, allowing them to enhance customer experience and to obtain valuable marketing insights: Implementing analytics inside the customer experience can provide several benefits to customer relationship management (CRM), as it shows greater efficacy in overseeing customers' perspectives across every touchpoint and recognizing areas of improvement (Zaki & Neely, 2019). According to the authors, this approach empowers organizations to build a customer-centric model that enables a deeper comprehension of customer behaviour and to understand how customers respond to the organization's endeavours to enhance the customer experience.

Moreover, predictive AI delivers several business advantages over traditional performance measures, such as accelerating issues' detection and resolution times, improving reliability, increasing forecasting accuracy, and reducing churn rate (Attaran, M., & Attaran, S., 2019). Moreover, they also show great potential if employed to predict customer behaviour: as consumers' activity can change swiftly in reaction to new needs or situational factors, analytical predictions have great relevance when dealing with behavioural phenomena (Surendro, 2019). All these technical advantages are then reflected in public perception of artificial intelligence: Kelley et al., (2021) have proven how a prevailing sentiment is that AI will exert a profound influence on society, and there is concrete backing for the responsible development and utilization of AI, being respondents prevalently excited and optimistic about the technology's benefits, and quite worried about its downsides.

Moreover, as introduced in the previous chapter, relying exclusively on consumer metrics such as CSAT or NPS is likely to provide an incomplete picture of customer experience: hence it should be necessary to incorporate a robust analytic methodology to measure customer sentiment, by taking advantage of users' wide feedback data (Gallagher et al., 2019). Machine learning models are proven to be capable of predicting customers' potential churn with optimal accuracy, providing the motivations underlying their decisions (Sabbeh, 2018). Additionally, another plus point that calls into question surveys' adequacy is given by their low average response rate: According to Baruch & Holtom, (2008), who investigated response rates among almost 500 studies of academic journals, the average rate in studies that use data collected from individuals is around 50%, whereas studies employing data from organizations show an average response rate of 35.7 percent. This shows a concrete limitation of traditional satisfaction measures, which are bound to individuals' discretionary power and willingness to answer questionnaires.

Given that nowadays 80% of data are unstructured (without a predefined format, mainly text derived from social media, reviews, video, and audio files), text mining techniques are essential in order to turn this data into a structured version, exploitable to make analyses and generate insights (IBM). According to McColl-Kennedy et al. (2019), incorporating text mining techniques into CX measurement (combining quantitative and qualitative data from various sources) empowers companies to better understand and manage customer experience, being CX analytics able to provide highly relevant insights. Furthermore, Natural Language Processing, (a component of text mining (Expert.ai, 2020)) is proven to measure users' satisfaction showing similar results to the ones obtained from ordinary questionnaires (Nwakanma et al., 2020), emphasizing the capacity of machine learning to analyze and forecast satisfaction basing on extensive databases of sentiments or reviews.

As a matter of fact, various academic initiatives with noteworthy outcomes can be encountered about the implementation of machine learning models to predict customer satisfaction for various businesses, such as hospitality (Oh et al., 2022), healthcare (Chatterjee et al., 2021) or e-commerce (Wong & Marikannan, 2020). This reinforces the ongoing trend of a potential transition to a predictive measurement of customers' sentiment, as performance measurement techniques are called to adapt to a modern data environment in which we all reside. At the same time, assessing the credibility of these tools over traditional and commonly used techniques requires an in-depth analysis of specific psychological dimensions affecting users' relationship with the technology: clarity and technical understanding play a pivotal role in establishing the final reliance on these technologies, thus further investigation is required around this relationship.

2.1.2 The road towards credibility: the roles of trust and understanding

A starting feeling to investigate inside this context is the concept of trust: as we mentioned in the previous chapter, a significant percentage of users lack concrete knowledge and awareness about artificial intelligence, influencing trustworthiness and the resulting credibility of the technology. As a matter of fact, trust is a crucial objective to be accomplished, both for personal and commercial relationships, as companies look forward to building a bond with their customers to retain them over time. Indeed, trust can be considered a key driver of customer retention and positive word of mouth, suggesting how an intense emotional reaction like trust drives consumers to share positive feedback on their service provider (Ranaweera, & Prabhu, 2003). Confidence forms the cornerstone of societies, economies, and sustainable progress: As a result, the complete potential of AI can only be unlocked by individuals, organizations, and societies when confidence is instilled in its creation, implementation, and utilization (Thiebes et al., 2021).

However, establishing trust for certain innovations resembles a very complex challenge for organizations: According to Ryan (2020), trustworthiness is a feeling that can be hardly accomplished for complex technologies such as AI, while it is possible to build solely a sense of reliance: AI cannot be trusted in the most common definitions of trust, lacking emotive and affective traits. Following this perspective, reliability can be an achievable goal for AI applications, while trust requires further effort to be established.

As a matter of fact, trust is a very complex construct, as after its initial formation it needs to be developed on a regular basis. According to Siau & Wang (2018) building trust is an evolving procedure that involves moving from immediate to continuous trust improvement: continuous trust will be based on how well the intelligence performs and accomplishes its purpose. Furthermore, the authors state that trust-building will be facilitated by AI applications that are simple to use, dependable, and capable of collaborating and interacting well with humans: AI applications should then be social, encourage human bonding, offer good security and privacy safeguarding, but also provide explanations of why decisions or actions were made (Siau & Wang, 2018). Moreover, trust plays a pivotal role not only in AI's acceptance, but also in influencing the final credibility and accuracy of its application: obtaining trust ensures that the processing of personal data is perceived as transparent and legitimate, but also fosters levels of credibility and robustness of algorithmic solutions (Shin, 2022).

As a matter of fact, general sentiment and opinions about artificial intelligence are quite heterogeneous, as one-third of people still lack a clear understanding of what AI is, and only half of users trust companies that take advantage of AI compared to other organizations (Ipsos, 2022). This shows how further efforts are necessary when it comes to explaining AI systems functioning, by also providing assurance on ethical treatment of users' data. In order to be accepted, AI needs to meet minimum standards, such as interpretability, which pertains to the ability to present explanations using language that is comprehensible to humans, and *explainability*, which encompasses ease and accuracy of interaction between humans and the technology. (Gilpin et al., 2018).

Indeed, the road towards the acceptance of AI (and its implementation inside customer experience) depends on individuals' and companies' ability to interact with algorithms properly, focusing on different psychological dimensions affecting the exchange. AI implies a collaborative relationship, inside which individuals' cognitive capabilities interfere with algorithms' outstanding computing power, in order to deliver the best possible solutions (Kaur et al., 2022). As a result, in order to increase usage and acceptance of AI decisions, consumers need to have a clear understanding of its functioning and capabilities, by developing an easily explainable and acceptable system: the ease of explaining AI's capacities to various stakeholders influences perceived levels of safety and trustworthiness and requires the involvement of different fields of knowledge such as data and computer science, but also economics and sociology (Kaur et al., 2022).

Furthermore, Shin (2022) states how trust's influence on credibility is stronger when users possess adequate expertise regarding the algorithm's functioning, showing how knowledge can boost positive outcomes inside the interaction: being AI an abstract and non-anthropomorphized form of intelligence, its perceived reliability and capacity to measure certain phenomena must face several barriers connected to its low awareness and technical understanding. According to Samek & Müller (2019), due to their complex structure, machine learning algorithms are generally perceived as "black boxes", that do not provide sufficient explanations about what leads toward their final prediction: Additionally, this need for transparency and technical understanding is stronger when algorithmic decisions might affect personal health or safety, highlighting a need for differentiated considerations according to the context and type of service delivered to consumers.

As a result, building clearly understandable AI systems resembles a key goal in order to maximize its outcomes: indeed, explainable AI (XAI) strives to facilitate human comprehension of the rationale behind machine decisions and the degree of their reliability and provides a framework for connecting machine intelligence with human intelligence, all with the intention of promoting and broadening the adoption of AI systems among human users (Angelov et al., 2021). Moreover, for machine learning systems to gain broader approval within a doubtful population, it is essential for these systems to possess the capability to offer adequate explanations for their decisions (Gilpin et al., 2018): being Artificial intelligence recognized as a complex and evolving technology, experts in the field shall operate while considering users' level of expertise in the technology, the required specifications in order to facilitate the understanding of the rationale behind a certain prediction and the safeguard of data privacy.

Furthermore, in the realm of artificial intelligence, the degree of confidence in the reliability of AI system attributes diminishes as the level of expertise of the individual interacting with these systems decreases, as the process of gathering and evaluating such evidence is more straightforward for the data scientist who designed the AI system compared to an end user who lacks training in data science (Ferrario et al., 2020). As a result, the absence of transparency and interpretability resembles a downside of artificial intelligence applications, as the reasoning behind model-based decisions is a key driver of trust for users (Došilović et al., 2018). Indeed, in order to make AI applications perceived as credible and beneficial, an adequate level of understanding and explainability of the technology is required, as it seems evident how users look for a clear and simple interaction with AI solutions. Developing customer-centric explanations by posing users pertinent questions in an appropriate manner, is a fundamental requirement for effective interaction, and requires in-depth investigation (Samek & Müller, 2019).

Furthermore, assuring users by endowing them with structured reasoning backed by simple evidence, helps make the system be perceived as safe, especially for sectors in which data safety is felt as critical (McDermid et al., 2021): According to the authors, machine learning-driven systems shift decision-making away from humans, highlighting the necessity to give proof that this transition is suitable, accountable, and secure: offering explanations for ML models and the predictions they generate can be included as a component of this supporting evidence. Exploiting AI for decision-making purposes, despite leading to more objective and direct decisions, still needs to become more understandable and ethical to humans in order to exploit its full potential (Lepri et al., 2021).

All these evaluations lead to a relevant approach to managing AI applications, known as Human Centred Artificial Intelligence, which tries to solve issues related to AI's trust and credibility. According to Shneiderman (2020), the exchange between humans and artificial intelligence is successful when users are endowed with high levels of control together with a high level of automation: well-designed automation provides users with a simple explanation of the algorithm's functioning and personal influence upon it, thus increasing its overall performance. Shneiderman (2020) additionally states how this approach improves AI's perceived reliability by employing algorithms' immense computational capabilities while preserving human intellect and decisional power. In addition, endowing low-expertise users with a concrete narrative about the model enables them to decide whether a machine learning prediction can be considered accurate, but also improves their overall psychological attitude towards the prediction (Biran & McKeown, 2017).

Lastly, the relationship between users' understanding of artificial intelligence and its final perceived credibility is reinforced by Rai (2020), who affirms how the information provided about an AI system affects users' trust and subsequent perceptions related to prediction. Thus, transparency has to be undoubtedly considered as a vital driver of consumers' trust: providing simple and effective explanations about the model's functioning and components will facilitate the acceptance and reliability of the prediction and become a competitive advantage for the implementation of AI solutions.

Following all these evaluations, it seems feasible to extend this paradigm to performance measurement, and in particular to the analysis of customer sentiment through machine learning techniques. Considering all the advantages of measuring users' sentiments using AI technologies, the replacement of traditional satisfaction surveys is becoming a feasible option for the near future. However, as we learned from existing literature, users' levels of clarity and understanding of how the prediction is obtained and how the model works influence final perceptions of trustworthiness and credibility. Consumers are more likely to place trust in AI predictions and accept companies' use of these techniques for marketing purposes if the systems' functioning is easily explainable and understandable. As it involves the disclosure of personal data, the relationship between AI and consumers is affected by psychological factors, such as the perceived intrusiveness of this type of technology.

2.2 The relationship between *explainability* and perceived intrusiveness

Despite credibility being an achievable goal for AI applications by meeting adequate standards of *explainability*, several ethical issues still arise regarding the perceived intrusiveness and potential violation of the personal sphere. It is well acknowledged how these technologies cannot operate without users' data, which has become the primary fuel that feeds AI systems' engines on a constant basis: as we all live inside a data environment, processing of personal data for business purposes has become an ordinary practice, yet when it is not conducted with adequate transparency users may perceive the interaction with the technology as detrimental or harmful. For this reason, it is important to learn more about the reasons underlying these potential psychological concerns. Since we believe that users' perceived intrusiveness may hinder the final credibility of the AI solution, we developed our second hypothesis:

H2) *Perceived intrusiveness mediates the relationship between the level of explainability (clarity: explicit vs implicit) and the perceived credibility of implementing AI to predict customer satisfaction. Specifically, an explainable implementation of AI (explicit level) influences more positively the perceived intrusiveness than the unexplainable one (implicit level), reducing its levels.*

2.2.1 AI ethics: contextual relevance and impact on users

Despite AI's impact on society and business being extremely beneficial, several ethical aspects currently undermine its perceived trustworthiness: as mentioned before, privacy and safety concerns have a central role when it comes to AI's acceptance, and in order to avoid psychological concerns the technology needs to comply with different rules and laws, moral values and principles, but also be robust and technically reliable (Jain et al., 2020).

As a matter of fact, ethics play a crucial role inside AI's context, being a key driver of the technology's acceptance: indeed, artificial intelligence highly necessitates novel safety assurance measures and the incorporation of ethical considerations into its systems (Bostrom & Yudkowsky, 2018). AI ethics, which encompasses a mix of values, principles, and methods necessary to guide AI technologies' utilization under moral standards, is necessary nowadays in order to counter all the potential individual and societal damages that may arise due to the improper use, abuse, inadequate design, or unintended negative consequences of AI systems (Leslie, 2019).

AI-related ethical problems have become extremely troubling for people, and the study of AI ethics has grown in importance both as a research area and as a subject of general interest for people, organizations, nations, and society (Huang et al., 2022). GDPR itself, the General Data Protection Regulation valid for all European citizens, since 2016 establishes obligations for all organizations collecting and utilizing consumers' data under seven guiding data protection principles (GDPR.Eu). Transparency is a core principle inside the

GDPR, stressing how data should be always processed in a fair and lawful manner, respecting individuals' privacy and safety. However, ensuring transparency for complex technologies such as AI systems resembles a much bigger challenge, as it involves decisions on both how and what to display to users (Felzmann et al., 2019).

As a result, particular attention is necessary in order to ensure an ethical interaction between users and artificial intelligence: Despite existing efforts to establish ethical guidelines for AI's adoption, further ways in which AI can behave ethically when providing solutions to humans and effectively convey their ethical judgments are needed (Yu et al., 2018). Ethics should therefore be built a priori inside AI systems, leveraging the expertise of engineers, by establishing a worldwide and harmonized AI regulatory framework that leverages interdisciplinary knowledge to tackle ethical concerns (Erdélyi & Goldsmith, 2018).

2.2.2 AI's invasion of the personal sphere: threats and privacy risks

AI's exponential evolution and the growing number of applications affecting companies' practices and people's everyday lives ended up affecting individuals' personal spheres. According to Coeckelbergh (2019), a starting issue relates to users' lack of awareness of whether their data are being collected or not, as oftentimes data collection practices are unclear or hidden. Since oftentimes users do not possess knowledge of how an AI machine reaches a certain outcome, AI's opacity can lead to concerns regarding its compliance to social or legal norms (Manheim & Kaplan, 2019).

Furthermore, Leslie (2019) outlines a set of potential harms and related consequences of AI on individual safety: when decisions or predictions are autonomously produced by AI systems, individual autonomy can be put in danger; irresponsible data management can lead to direct harm to both the general welfare and the well-being of individuals, but also damage public confidence in the ethical application of AI innovations that benefit society; additionally, an overabundance of automation could diminish the necessity for human-to-human interactions, while algorithm-driven hyper-personalization, might lead to increased polarization in social relationships by constraining our exposure to diverse worldviews; lastly, invasion of privacy can potentially undermine individuals' fundamental right to pursue their objectives and life plans without unwanted external influence.

Another critical issue is connected to data security: being systems increasingly interconnected, risks of data breaches and hacking are always around the corner, and users are forced to trust companies' data infrastructures without knowing the exact levels of structural safety (Coeckelbergh, 2019). Indeed, it is common thought both among Americans and Europeans that artificial intelligence requires careful management, as respondents express significant worries regarding the enduring effects of advanced AI (Zhang & Dafoe, 2019): Primary concerns encompass data privacy along with AI-boosted cyber assaults, monitoring, and digital manipulation.

An essential condition for artificial intelligence not to harm the personal sphere of users is that it does not pose direct harm or risk to them: the principle of nonmaleficence in AI primarily involves ensuring that AI systems do not cause harm to humans or have adverse effects on them, by safeguarding mental and physical well-being and ensuring that AI systems are not susceptible to malicious exploitation. (Huang et al., 2022).

Moreover, low confidence in AI solutions can be caused by biased and incorrect outcomes: data analysis can produce erroneous results due to algorithmic limitations or biased sampling, leading to AI-driven decisions that, contrary to common belief, can increase human biases, posing substantial risks to equality and democracy. (Manheim & Kaplan, 2019). As a result, artificial intelligence's outcomes cannot be considered an incontestable source of truth, and it is therefore evident how knowledge is such a powerful instrument to endow users with when interacting with AI systems, as it influences their experience and overall acceptance of the technology. However, being the subject extremely complex and technical, reaching appropriate levels of understanding and acceptance still resembles a complex challenge.

A low understanding of such matters belongs not only to end users but also to professionals writing about artificial intelligence: oftentimes contents such as AI implementation and ethical frameworks are not treated accurately, providing incoherent and misleading explanations (Ouchchy et al., 2020). Additionally, Zhang & Dafoe (2019) affirm that understanding and support for AI development is highly correlated to users' demographic characteristics, such as age, gender, and wealth: higher income, education, and expertise levels are connected to higher acceptance of such technologies. All these considerations lead to an indisputable need for clarity and accuracy in order to avoid psychological concerns about these technologies.

2.2.3 Explainable AI: advantages and mitigation of risks

As mentioned before, explainable AI presents several advantages, not only related to the mere technology's understanding but also to its acceptance and avoidance of users' psychological concerns. Considering that machine learning-based systems are moving decisional power out of human control, providing assurance about the safety and reliability of this handover is a necessary step to respect and safeguard individuals' personal sphere.

As a matter of fact, AI and machine learning models are still impractical and not explainable, generating concerns that impede their final adoption (Tantithamthavorn & Jiarpakdee, 2021). Explanatory information helps provide explanations for events, reduces uncertainty, and mitigates misunderstandings by simplifying the process of generalizing and producing conclusions (Lombrozo, 2011). Current machine learning algorithms can generate complex predictions, yet the sophistication lying behind their outstanding abilities complicates the understanding of the results (Adadi & Berrada, 2018). Due to their non-linear structure, machine learning and artificial intelligence models are typically employed as a "black box", with no accurate specification of the factors that drive their predictions (Samek et al., 2017): Explainable AI is, therefore, a much-needed requirement in order to establish adequate trust, and this lack of transparency can therefore present a significant drawback for users' interaction with AI.

McDermid et al., (2021) propose an effective framework for explainable AI, which involves providing specific interpretations for each phase of the AI model to all involved stakeholders, in order to reach an effective final *explainability* (Fig. 1): Explainable AI therefore aims to offer human-understandable representations of machine learning models in order to assist in overcoming interpretation struggles, which are proven to be a probable driver of psychological concerns from the user side.

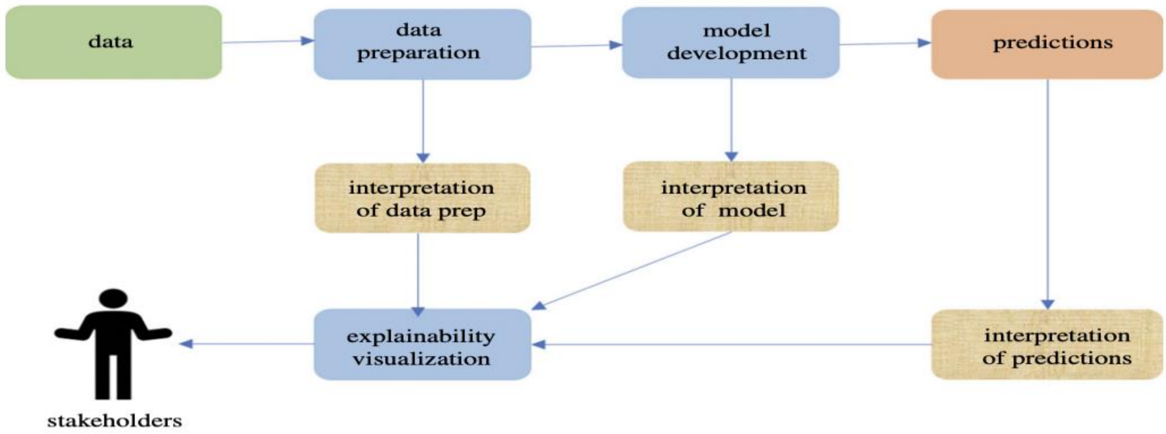

Figure 1 – AI system phases' interpretation and explainability
Source: McDermid, J. A., Jia, Y., Porter, Z., & Habli, I. (2021)

Justifying a process by providing concrete causal and logical explanations of its outcomes offers substantial benefits for the avoidance of psychological concerns: providing concrete reasoning around an AI-driven prediction influences users' acceptance of the algorithm's outcome (Binns et al., 2018) while helping to reach an appropriate level of confidence in the technology. In addition, explainable AI allows individuals to exert a higher level of control and autonomy towards the model, facilitating the overall assurance and acceptance of the technology (McDermid et al., 2021).

As explained previously, artificial systems are affected by bias just like humans, and for this reason, explainable AI has the potential to help identify elements that could have led to an unjust and morally questionable outcome, with the aim of either removing these elements, reducing their impact, or acknowledging their presence (Langer et al., 2021). Furthermore, Samek et al. (2017) outline the main benefits deriving from explainable AI, such as: increasing the effectiveness and validation of AI outcomes, delivering more easily improvements to the system, observing effortlessly existing data patterns, and complying more strongly with legal constraints. Thus, explainable artificial intelligence not only offers countless advantages from the user side but also provides tangible enhancements to companies' AI systems, enabling timely adjustments by leveraging on a smoother interaction with their customer base. For this reason, specific actions are necessary in order to optimize the interaction between artificial intelligence and individuals, to reach positive outcomes at the end.

Nevertheless, in order to reach all the desired outcomes and ward off users' concerns, explainable AI has to pay attention to its form and the way in which information is presented to all involved stakeholders: According to Adadi & Berrada (2018), a key requirement to ensure a positive and beneficial exchange between AI and its users, is the level of interaction, being individuals in search of interactive explanations that can help them understand the system's functioning and the rationale behind its outcomes. Being oftentimes AI and machine learning models able to produce predictions autonomously, individuals are looking for additional touchpoints, in order to perceive the technology as more familiar, while interacting in the first person. As a result, particular attention must be placed on the quality and characteristics of the information provided to individuals.

Explanatory information for AI solutions can be presented in different formats, according to explanatory objectives and visual preferences: Information can generally be presented in two main ways, text-based, which simply uses natural language text, or multimedia, which includes graphic elements such as images or animations (Gregor & Benbasat, 1999). According to Marques-Silva & Ignatiev (2022), the most common AI explanations fall short of offering convincing justifications, often providing redundant and futile information: For this reason, formal and structured explanations are required in order to empower users to understand concretely artificial intelligence's functioning. Decisions will then be taken according to context and people's preferences, as individuals generally look for simple information, that matches their desired necessities (Langer et al., 2021).

As a result, providing the right information and reaching an adequate level of *explainability* is essential in order to avoid users' psychological concerns, such as the intrusion of the personal sphere. At the same time, finding the right solution to convey this information requires accurate evaluations, which concern the choice of the visual elements to be included in the presentation, but also the informative content to be communicated to the user about the system's functioning. As users are increasingly exposed to the disclosure and processing of personal information for marketing purposes, individuals have also started to place huge importance on their own data protection: a low level of explanation and clarity on the outcomes (predictions, decisions, analysis) delivered by AI systems' can generate concerns about unethical behaviours. These conditions are essential in order to generate sentiments of trust and acceptance towards the technology, which in turn will foster its final credibility and final replacement of traditional methodologies. Since we believe that intrusive concerns may influence negatively the final perceived credibility of predicting customer satisfaction using AI, we developed our last hypothesis:

H3) *Perceived intrusiveness mediates the relationship between explainability (explicit vs implicit) and perceived credibility. Specifically, a lower level of perceived intrusiveness leads to a higher perceived credibility by users.*

2.3 Psychological concerns and intrusiveness impact on credibility

As investigated so far, it is clear how understanding and *explainability* of artificial intelligence play a crucial role in the acceptance and trust of its application; furthermore, we have acknowledged how the provision of clear and effective information mitigates individuals' potential concerns, such as the intrusion of the personal sphere. For this reason, it is important to explore how these feelings can affect the final credibility of an AI solution. As a matter of fact, privacy concerns are one of the main obstacles hindering the adoption of innovative technologies (Li et al., 2018), pointing out how credibility will be hard to achieve if the interaction with a given technology produces intrusive feelings from the user side.

AI systems indeed often unintentionally challenge the expertise and capabilities of individuals, and concerns related to threats and self-evaluation are likely to hinder the acceptance of this technology (Elkins et al., 2013). Additionally, many individuals exhibit reluctance to engage with AI systems because of the influence of social-cognitive processes that shape human interactions with the technology, with warmth and competence being crucial factors that depend on human-AI relationship (McKee et al., 2021).

According to Gillath et al. (2021), trust-building for AI technologies shows a similar path to real human-to-human relationships, as enhancing security perceptions increases final reliance on artificial intelligence. As a matter of fact, generating trust and credibility in complex technologies is a very complex task, thus perceived safety during the interaction plays a central role: avoiding issues such as abuse or misuse of artificial intelligence solutions, which could, in turn, affect negatively individuals, is a key driver of final trustworthiness (Jacovi et al., 2021). Furthermore, to establish trust it is essential for AI to bring tangible benefits to humans, being applied for social good and enhancing the quality of life (Varshney, 2019).

Therefore, it is clear how to install credibility and reliance on AI solutions not only is required model's technical efficiency and predictive accuracy but also a pleasant interaction that places importance on individuals' psychological needs. To further highlight the relevancy of complying with ethical guidelines for human-AI interaction, Textor et al. (2022) state how unethical behaviors not only bring negative perceptions but also can damage trust; additionally, the consequent distrust in the technology is a hard consequence to mitigate through apologies or adjustments, showing how crucial it is to prevent as a rule users' psychological concerns. Indeed, individuals expressing privacy concerns about artificial intelligence are more inclined to oppose the application of the technology (Lobera et al., 2020), highlighting how users who manifest worries about AI's intrusiveness should be less prone to manifest trust and credibility toward its application.

As a result, it is reasonable to assume that explainable artificial intelligence is a necessary condition for users to perceive the interaction with the technology as positive and beneficial, but also to ensure that the outcomes produced by the AI model are perceived as reliable and accurate. Users' potential concerns and the perceived intrusion of the personal sphere are then crucial discriminant factors that could hinder the perceived credibility of a given prediction delivered by an AI model.

Considering the literature analyzed so far, the resulting research questions that this experimental study aims to answer are: How does the perceived credibility of implementing AI to predict customer satisfaction change in relation to users' perceived intrusiveness? How does the level of *explainability* (explicit or implicit) of the AI solution affect users' perceived intrusiveness? Does a lower perceived intrusiveness lead to a higher level of perceived credibility?

2.3 Conceptual framework

The main objective of this experimental study is to investigate how different levels of AI *explainability* (explicit vs. implicit), influence perceived credibility when implementing this technology to predict customer satisfaction. To test this relationship, it was decided to complete the conceptual framework through the indirect effect represented by the mediating factor related to perceived intrusiveness. Following this assumption, it was decided to implement the research model using a mediating factor represented by intrusiveness, an independent variable related to AI *explainability*, and a dependent variable related to perceived credibility. Therefore, Andrew F. Hayes' Model 4 was adopted for the development of the conceptual framework, which results characterized by an independent variable (X) a dependent variable (Y), and a mediator (M).

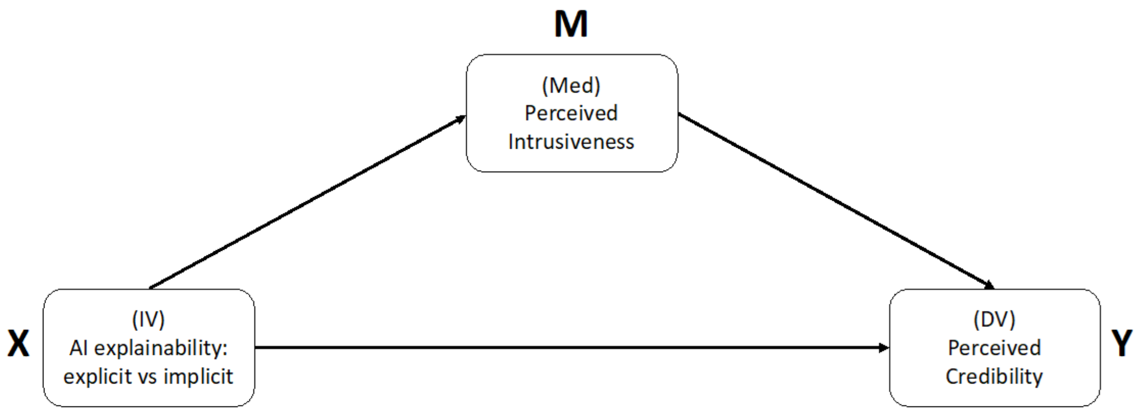

Figure 2 - Conceptual model

Chapter 3: Experimental Research

3.1 Methodological approach

3.1.1 Methodology and Study

The following study consists of a conclusive and causal research design between subjects (2x1). The results of the experiment are coming out from the answers obtained from a questionnaire included in a self-administered survey, carried out in Italy during August 2023, using the online platform Qualtrics XM.

The survey's participants have been selected with a non-probabilistic sampling method, specifically, a convenience sampling method was used in order to leverage the speed and ease of access and selection of the elements of the population. Indeed, this technique is optimal for our research purposes being cost-free and allowing us to collect data rapidly and with a high response rate.

Considering our target sample, no demographic restrictions have been applied, collecting data both from male and female respondents, as demographic variables were not considered to influence a priori in a statistically significant way the results of the experiment.

3.1.2 Participants and sampling procedure

Respondents of the survey have been contacted using an anonymous link created by Qualtrics XM, which was subsequently shared through social media networks and instant messaging apps, such as Instagram and WhatsApp. The survey was administered to 155 individuals, out of whom 153 individuals actively engaged in the study, providing complete responses to all the questions in the questionnaire. The remaining 2 incomplete responses have been excluded from the dataset after the data cleansing procedure.

The surveyed population mainly consisted of master's degree students or recent graduates from Italy: thus, the respondents' average age was 26,27, while the minimum and maximum age detected were 18 and 60. Focusing on gender, the majority identified as male 56,2 % (86/153), while females accounted for 41,8% (64/153) out of total respondents; the remaining 2% (3/153) avoided specifying their gender.

3.1.3 Data collection and questionnaire composition

In order to conduct the experimental study, it was necessary to develop an 8-question questionnaire with 6 specific questions and 2 demographic questions.

It was necessary to generate two different visual stimuli in order to manipulate the independent variable (AI *explainability*: explicit vs. implicit): the first scenario was characterized by an image of a post-purchase banner, which informs how customer satisfaction will be predicted by artificial intelligence, without providing any explanations or details about the data collected and methods used.

Figure 3 - Condition 1 (Implicit – Unexplainable AI)

The second scenario turns out to include an illustration of a post-purchase banner, which informs how customer satisfaction will be predicted by artificial intelligence, specifying all data collected from users, giving details of the AI model, and ensuring the respect of GDPR and data consensus.

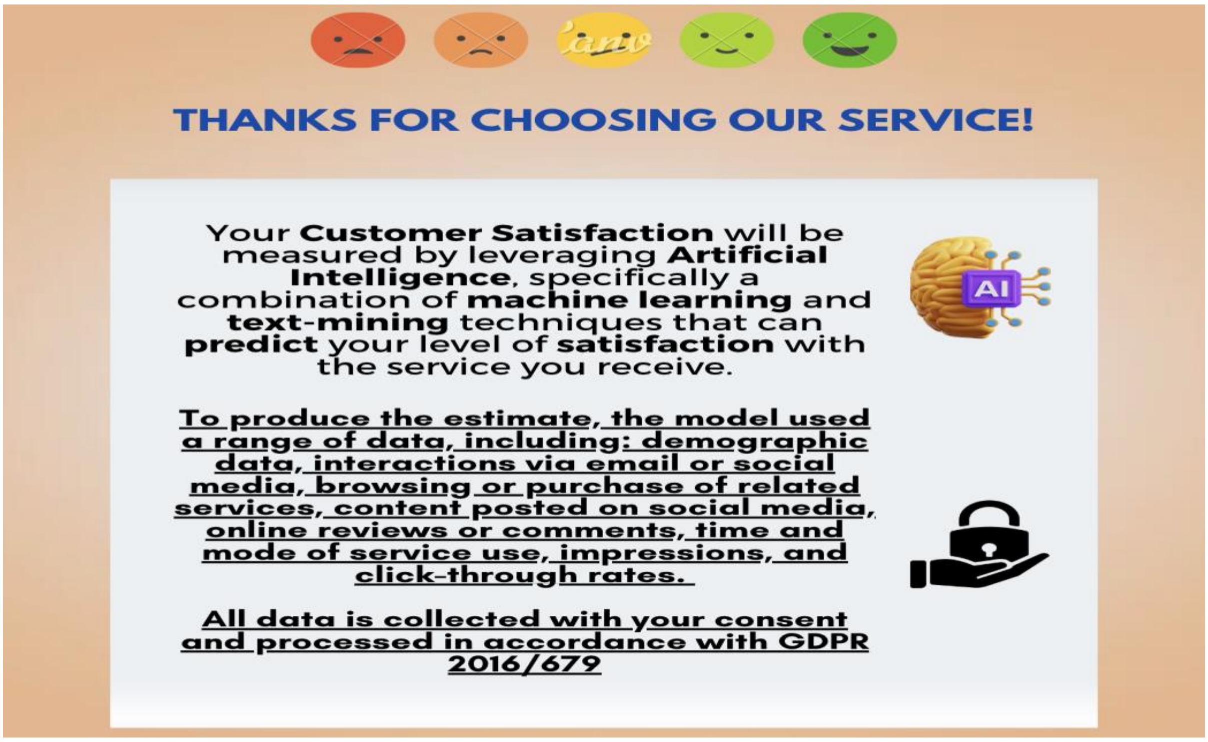

Figure 4 - Condition 2 (Explicit – Explainable AI)

As was previously noted, a questionnaire was used to gather the data, and it was broken down into four key sections. A brief introduction and an explanation of the academic goal of the experimental research were included at the start of the questionnaire. Additionally, full compliance with privacy laws regarding the anonymity policy regarding data collecting and handling was preserved after including the university's credentials.

A random block of two distinct scenarios makes up the second section of the survey. In fact, a uniform distribution of exposure to both visual stimuli had only been achievable by applying randomization inside the overall structure of the questionnaire. To avoid potential cognitive bias and possible conditioning related to brand sentiment, both scenarios were represented by two mock-up simulations of post-purchase banners without any reference to real brands. Therefore, both simulations were carried out using Canva Pro, a graphic design platform.

The third part of the survey was introduced to respondents after they were subjected to observing one of the two scenarios. This block of the questionnaire consisted of 6 questions: the first 3 concerning the mediator (perceived intrusiveness) and the other 3 concerning the dependent variable (perceived credibility). All questions were scored using a Likert scale based on 7 rating points. The first scale, relating to the mediator, is derived from the scale pre-validated by Edwards et al. (2002). The second scale, related to the dependent variable, is derived from the scale pre-validated by Soh et al. (2009). Following the requirements of the experimental research, both scales were adjusted. The demographic question block, which includes inquiries on the respondents' age and gender, is found in the fourth and last section of the questionnaire.

3.2 Experimental results

3.2.1 Data analysis

In order to be analysed, data collected through the questionnaire of our Qualtrics XM survey have been exported inside the statistical software SPSS (Statistical Package for Social Science). As the first step, an exploratory factor analysis was conducted to examine and validate the items of the scales employed for our conceptual model; a principal component analysis was carried out as the extraction method, by applying Varimax as the rotation technique. After having observed the table of total variance explained, the number of factors to be extracted was determined; following the Kaiser rule, it was additionally verified that both eigenvalues were greater than 1 and that cumulative variance in percentage was greater than 60%. Specifically, all items showed an extraction value greater than 0,5 and a loading value greater than 0,3: as a result, all items composing the scales have been kept, validating them. Afterward, in order to prove the reliability of the employed scales, a reliability test was conducted: specifically, Cronbach alpha of both constructs was taken into consideration, assessing whether it was greater than 60%.

Focusing on the deployed scales, as the mediator's scale showed a value equal to X, and the dependent variable’s scale scored a value of Y, both scales can be considered reliable. Then, in order to assess sampling adequacy, a KMO test was conducted.

Focusing on the deployed scales, as the mediator's scale showed a value equal to X, and at the same time the dependent variable’s scale scored a value of Y, the sampling adequacy level can be considered adequate in both cases. Lastly, Bartlett's sphericity test was conducted, showing in both cases a p-value equal to 0.001 (p-value < α = 0.05), thus providing a statistically significant result.

3.2.2 Hypotheses results

From now on, the main hypothesis of the conceptual research model will be analysed in detail, with the aim of either confirming or rejecting their statistical significance, therefore assessing whether they were conceived appropriately. As a result, we will go through each hypothesis, analysing them in order.

H1

A comparison of means test was performed using a One-Way ANOVA as the method of analysis to assess the effect of the independent variable (AI *explainability*: explicit vs. implicit) against the dependent variable (perceived credibility). The analysis was performed to determine the statistical significance of the direct hypothesis (H1) in question. The dependent variable (Y) is metric in nature, while the independent variable (X) is nominal and categorical in nature, and is divided into two different conditions, coded with 0 (Implicit) and 1 (Explicit). The group of respondents exposed to the scenario coded with 0 (78 individuals) had a mean value of 2.1197, while the respondents exposed to the visual condition coded with 1 (75 individuals) had a mean value of 5.6889 observed. This was evident from the descriptive statistics table after the ANOVA was conducted. The ANOVA table also showed a p-value for the F-test of 0.001, which was statistically significant (p-value < α = 0.05) after being taken into account.

As a result, the averages of the groups differed with statistical significance, confirming the impact of X against Y. As a result, the major effect, or direct hypothesis H1, was validated.

H2-H3

To test the statistical significance of the indirect hypothesis (H2-H3), a regression analysis was conducted through the application of Model 4 of Process Macro version 3.4.1, developed by Andrew F. Hayes to test the mediation effect caused by intrusiveness against the relationship between the independent variable (AI *explainability*: explicit vs implicit) and the dependent variable (Perceived credibility). To test the success of the mediation effect, it was necessary to distinguish it into two different relationships: a first effect between the independent variable and the mediator (H2) and a second effect between the mediator and the dependent variable (H3). Specifically, to demonstrate the statistical significance of both hypotheses, a 95% confidence interval was adopted with an α reference value of 5%. In addition, it was necessary to make sure that the extremes of the confidence range (LLCI=Lower Level of Confidence Interval; ULCI= Upper Level of Confidence Interval) for each hypothesis met the sign concordance (both positive or negative) as the zero must not be contained within the interval. Finally, to evaluate each effect's sign and magnitude (direction and strength), the β coefficients of the regression analysis of both relationships between the variables were examined.

H2

After examining the SPSS output, it was possible to determine that the first part of the indirect effect exhibited a p-value of 0.0000, a good confidence interval (LLCI = -3.6616 ULCI = -2.9261), and a negative regression coefficient **β** of -3.2938. As a result, it was determined that this section of the indirect effect was statistically significant, corroborating hypothesis H2.

H3

As for the second part of the indirect effect, through observation of the SPSS output, it was possible to note a p-value of 0.0000, a favourable confidence interval (LLCI = -0.8817 ULCI= -0.6783), and a negative regression coefficient **β** of -0.7800. Therefore, this section of the indirect effect was found to be statistically significant, confirming hypothesis H3.

Considering the results of the study, it was possible to establish the overall success of the mediation effect (indirect effect) by detecting a partial mediation, given that both sections of the indirect effect turned out to be statistically significant.

3.3 General discussion and conclusion

3.3.1 Theoretical contributions

The main goal of this research was to explore how explainable artificial intelligence (which involves providing clear and detailed information about the functioning of an AI model and the related data collected from people) influences users' perceived credibility of an AI solution, employed specifically to predict customer satisfaction in our case. This research project aims to investigate the potential replacement of traditional Customer Satisfaction surveys by innovative predictive methods based on artificial intelligence.

In order to do so, we developed three different hypotheses: the first one concerns the main effect between the independent variable (AI *explainability*: explicit vs. implicit) and the dependent one (perceived credibility), while the second and third are related to the indirect effect produced by *perceived intrusiveness*, our mediation factor. After having collected data using a questionnaire from an online survey and analysing the results on the statistical software SPSS, our three hypotheses were confirmed.

The first hypothesis (H1) relates to users expected positive and higher perceived credibility when interacting with an explainable AI solution, which provides information on the techniques and data employed to produce an estimate, compared to an unexplainable one, which keeps hidden its functioning and methods. Being (H1) confirmed, it is reasonable to state that when an AI solution is explainable and provides clear information its perceived credibility and users' reliance is fostered. Specifically, explainable AI directly affects the level of reliance on artificial intelligence employed to predict customer satisfaction instead of traditional surveys: the clearer explanations will be provided to users, the more credible and reliable its implementation will be.

The second hypothesis (H2) concerns how perceived intrusiveness mediates the relationship between the level of *explainability* and the perceived credibility of implementing AI to predict customer satisfaction: Given that also (H2) was confirmed, it is confirmed how explainable AI (explicit) lowers the level of perceived intrusiveness compared to unexplainable AI (implicit). Users who receive information about the AI model functioning and details about data collection and processing are less prone to perceive the interaction as intrusive: Endowing knowledge and explanations around an AI solution can mitigate intrusiveness concerns, which in turn impact the final perceived credibility of the implementation.

The last hypothesis (H3), which explores how perceived intrusiveness mediates the relationship between *explainability* (explicit vs. implicit) and perceived credibility, confirms how a lower level of perceived intrusiveness leads to higher perceived credibility by users. The results validate that individuals who do not detect intrusive concerns around implementing AI to predict customer satisfaction perceive the solution as more credible and reliable.

This experimental study provides relevant findings about the implementation of AI methods to predict customer satisfaction as an alternative to traditional surveys. Being predictive artificial intelligence a growing field, whose applications are disrupting several business practices, further research is needed to explore its tangible impact on performance measurement and its concrete feasibility. Furthermore, the study broadens the benefits and the reach of XAI, a well-established branch of AI literature, highlighting how this framework facilitates the transition towards innovative technologies for customer experience measurements.

Considering the aforementioned literature, this study goes deep into the potential application and deriving benefits of XAI to enhance customer experience: Broad academic research can be encountered about XAI's relevance in safeguarding data safety, respecting AI ethics, and ensuring a positive human-technology interaction, yet additional research is required to analyse how this field can be applied to enhance the implementation of artificial intelligence for settled practices.

Moreover, the study takes into account consumers' psychology when interacting with artificial intelligence, demonstrating specifically how perceptions of intrusiveness of the given technology play a key mediating role between *explainability* and perceived credibility of the AI solution. As a result, the study resembles an attempt to prove the feasibility of the transition to predictive measurement of customer satisfaction powered by the implementation of AI technologies.

Explainable AI research, which has been significantly explored in chapter two, points out relevant follow-ups: Considering XAI's tangible advantages for artificial intelligence acceptance and adoption, this framework can be extended for different research purposes, exploring how its advantages can facilitate AI disruption of companies' most settled practices.

3.3.2 Managerial Implications

The main purpose of this research is to explore artificial intelligence's potential to disrupt customer experience measurement, in particular, how predictive AI techniques can potentially replace traditional customer satisfaction measurement methods. Specifically, the study aims to highlight how explainable AI can foster the perceived credibility of this shift, considering individuals' privacy concerns: providing clear and detailed information about an AI prediction facilitates users' reliance on technology, allowing in turn companies to adopt these technologies inside their processes.

Given the incontestable benefits that explainable AI models can bring to marketing purposes (Rai, 2020) and the broad influence across a wide range of application domains (Adadi & Berrada, 2018), several consequences can be outlined following the results of this study. As we learned from the literature, XAI delivers transparency, mitigates bias, and enhances reliability: Yet, based on the takeaways of this research, further business implications can be pointed out.

Being XAI an enhancer of artificial intelligence's credibility, companies should consider adopting this strategy to facilitate the implementation of AI into their processes, especially for practices that are still conducted with a low level of innovation, relying on traditional methods. As a matter of fact, predictive AI is increasingly becoming a strategic tool, especially for customer experience, and for this reason, companies will be called to gradually implement this technology inside their processes. The study's results highlight how unexplainable AI, an artificial intelligence-powered prediction that does not convey the necessary information to users, hinders significantly users' perceived credibility, undermining companies' ease of adoption of the given technologies.

Implementing XAI would benefit not only reliance from the user side, ensuring the respect of AI ethics and the safeguarding of individuals' data privacy, but also the employees' coexistence with artificial intelligence: an explainable model would then help employees understand how AI can enhance their decision-making and problem-solving capabilities and boost their productivity.

Focusing on performance measurement, it's important to highlight how certain indicators are still not influenced by AI, mainly due to their uncomplicated and manually measured nature: Therefore, explainable AI is an important component to facilitate the technological transition of those metrics, in case of a need for innovation. As acknowledged in Chapter 1, qualitative performance indicators mostly rely on subjective and non-numeric information, and for this reason, are inevitably related to human judgement and interpretation. However, considering AI's exponential rise and usage, it is possible to assume that in the future also non-quantitative metrics could end up being disrupted by AI models.

Following the results of the experimental study and the validation of our research hypothesis, explainable artificial intelligence can be considered a key enabler of credibility and reliance: thus, XAI could become a requirement when marketers might consider using artificial intelligence to measure qualitative aspects of customer experience. In order to do so, a required condition would be outlining a priori a structured set of information to provide to consumers, reflecting accurately on the content and visual elements to be included to deliver the best possible explanations to them.

As highlighted by McKinsey (2020), individuals manifest a different willingness to disclose personal data depending on the type of service and the related personal safety risks: As a result, developing differentiated information, with different requirements and levels of specification according to the business in which a company is operating could be an optimal solution to foster users' acceptance and reliance before implementing it. Thus, companies are called to place increasing attention on explainable AI, conveying clear and understandable information about the models deployed. Specifically, services that involve the treatment of sensitive data (such as finance, insurance, or healthcare) would require a higher level of explanation provision to reassure consumers that the processing of personal data for AI's predictive purposes is conducted fairly and safely. This could in turn help avoid consumers' resistance and diffidence of a prediction produced by artificial intelligence while helping companies to switch to AI solutions.

Moreover, a required step to follow before implementing AI to gain customer experience predictions could be investigating among the customer base the level of understanding and awareness of predictive AI techniques. Afterward, conducting educational initiatives with the aim of informing the customer base about artificial intelligence reliability and effectiveness to predict customer experience dimensions would be an effective strategy to mitigate individuals' diffidence and scepticism around AI, often related to a lack of knowledge of the subject matter.

Furthermore, given that anthropomorphism is proven to influence positively the human-AI interaction, mitigating anxiety from uncertainty (Kim et al., 2019), AI models delivering predictions could be endowed with human-like features, providing explanations about their functioning while interacting directly with users. This could help not only gain more attention during the explanatory phase but also ensure an augmented emotional and relational connection between individuals and artificial intelligence. All these recommendations could end up facilitating the interaction and collaboration between AI and human beings, building trust inside the relationship thanks to the benefits of XAI, and increasing users' satisfaction with AI solutions.

Organizations that put XAI at the core of their AI practices would facilitate both employees' cooperation with the technology, but also consumers' acceptance and understanding of AI's tangible benefits and effectiveness. Moreover, XAI would facilitate the transition to predictive measurement of customer experience (introduced in Chapter 1): these methods should not be considered as disrupting replacements for all settled measurement standards, but rather as additional tools to be integrated with already existing and functioning ones when perceived as necessary. Specifically, large companies which are called to deal with huge customer-bases, collecting and evaluating numerous service or product feedbacks, should consider implementing predictive AI to foresee certain dimension of experience's satisfaction and speed up their internal processes.

In conclusion, looking at the results of the study, explainable AI should become a competitive advantage for all companies that aim to implement artificial intelligence for customer experience measurements: XAI not only enhances understanding of the technology through transparency (Shin, 2021) but could also facilitate building brand trust for all the stakeholders who value ethics for AI practices. Lastly, this framework could help mitigate users' resistance to artificial intelligence, allowing companies to replace more easily in the future measurement techniques with AI solutions: Consequently, this transition would help improve decision-making, enhance operational efficiency, and speed up issue resolution.

3.3.3 Limitations and Future Research

This study presents relevant limitations that could be used in the future for future research on the topic. Considering that perception of artificial intelligence significantly varies according to the age of respondents, with younger generations more inclined to accept AI (Pelau & Nistoreanu, 2018), age could resemble a concrete limitation of our research. Being our survey mostly addressed to university students or graduates, with an average age of 26,27, future research might consider extending the investigation to older generations who might be less inclined to manifest acceptance and reliance on innovative AI solutions. Additionally, the sampling method used in this study presents concrete limitations, since it may include potential biases in respondents' selection and is not guaranteed to be accurately representative of the population.

Furthermore, as acknowledged by Zhang & Dafoe (2019), demographics are crucial in relation to the acceptance of AI technologies, as higher levels of income and education influence positively artificial intelligence's perception. As a result, demographic factors such as income, education, or occupation could be taken into consideration to broaden future research about the topic.

Another limitation resides in the nationality of the respondents, as the survey was solely addressed to Italian respondents: thus, this experimental study could be extended to foreign respondents to explore whether the perceptions of AI's credibility in predicting customer satisfaction and explainable AI's relevance depend on the country of origin of targeted individuals. Indeed, for the purpose of generalizing our conclusions, it may be beneficial to reproduce the research in various countries characterized by diverse cultural orientations. Interesting countries to be involved in the study would be the ones that are characterized by cultural propensity or adversity for artificial intelligence innovations, in order to detect significant geographical differences related to our research purposes.

In addition, another limitation of this study connects to the need for differentiated evaluations depending on the industry and type of service involved when dealing with artificial intelligence acceptance. Samek & Müller (2019) state that transparency requirements are stronger when algorithmic decisions affect individuals' safety or well-being. As a result, our conceptual model could be enriched by adding *service type* as a moderator variable between the dependent and independent one. The target sample was exposed to a scenario that did not specify the sector or type of service for which artificial intelligence was utilized to predict customer satisfaction. As a result, adding this specification would help investigate how different services, characterized by diverse safety risks and requirements could end up impacting the perceived credibility of explainable AI. As our two mock-up scenarios did not refer to specific brands, further research should consider involving specific companies, to investigate how explainable AI might be perceived as a requirement in relation to the product or service provider involved in leveraging artificial intelligence to extrapolate customer experience predictions.

Moreover, this experimental study was focused on investigating AI credibility in predicting customer satisfaction, yet research could be replicated by considering a different customer experience indicator, in order to see how perceptions of reliance vary according to the type of measurement conducted. Future research should also consider enriching the information presented in the stimuli and giving more details about the AI model, experimenting with different types and levels of *explainability*. Lastly, future studies might think of replacing the variables of our conceptual model, in order to explore further aspects of the research topic: the dependent variable *perceived credibility,* for instance, could be replaced by *purchase intention* to investigate how explainable AI might impact willingness to buy a given product or service for a company that leverages on predictive artificial intelligence. On the other hand, *perceived intrusiveness,* the mediator of our conceptual model, could be substituted with *brand trust*, to deepen how individuals' reliance on a company influences the final perceived credibility of predictive AI.

Abstract

Artificial Intelligence is reshaping business practices, providing valuable predictive insights through extensive data processing. Predictive AI is becoming a competitive advantage, influencing performance measurement and marketing KPIs, and hinting at a technological shift. Qualitative metrics, such as Customer Satisfaction, are less affected by this transition, yet require further academic investigation. Previous research examines how AI models can predict efficiently customer sentiment, and how explainable artificial intelligence (XAI) fosters acceptance and reliance on AI solutions: further research is needed to explore how XAI could become a key enabler of the potential predictive transition of customer satisfaction measurement. This experimental study investigates how implementing explainable AI affects individuals' perceived credibility of artificial intelligence deployed to predict Customer Satisfaction while considering the mediating role of perceived intrusiveness of given methodologies. Based on a questionnaire conducted through a self-administered survey with Qualtrics XM, data have been collected and then analysed with SPSS, validating the previously assumed hypotheses: the outcomes of the study confirm how explainable AI enhances perceived credibility of predictive measurement of customer satisfaction, based on AI models. Moreover, findings validate how XAI is helpful in mitigating individuals' perceived intrusiveness of predictive artificial intelligence, highlighting how a lower level of perceived intrusiveness induces greater reliance from the user side. Based on the study's results, XAI can be considered a potential enabler of the transition to AI-based predictive measurement of customer experience: companies are thus called to place increasing importance on information provision and to conceive effective ways to deliver information and explanations of how an AI model produced a certain prediction.

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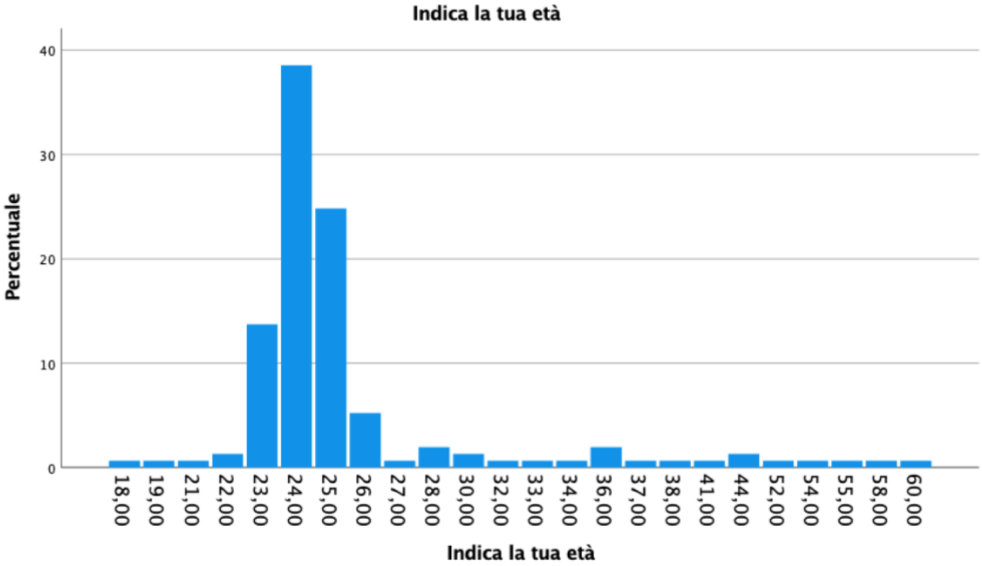
Appendix

Descriptive statistics: Age



Statistiche

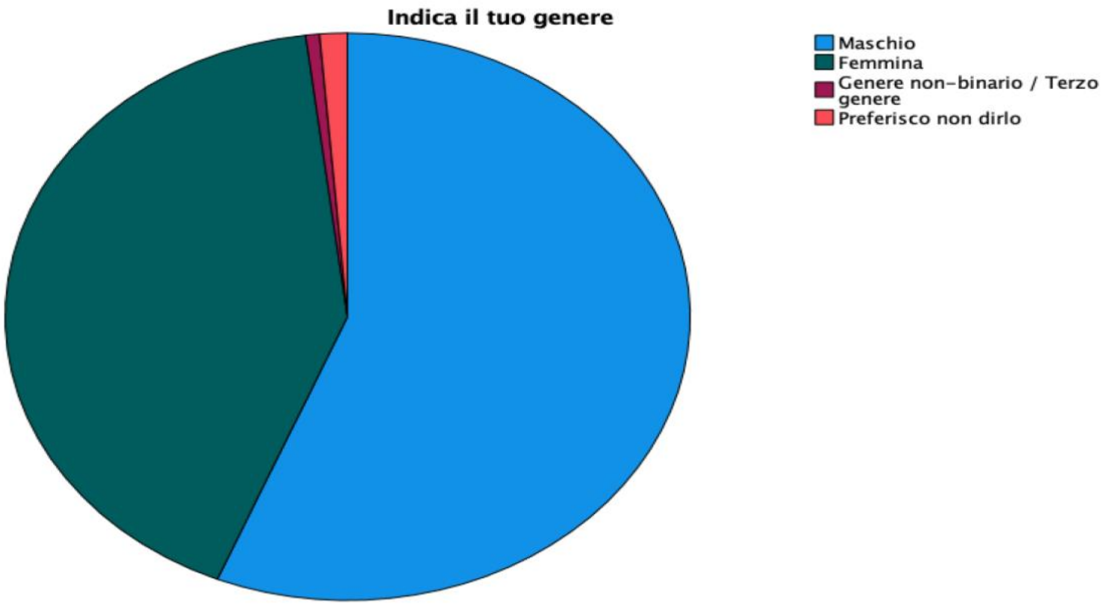
Indica la tua età

N	Valido	153
	Mancante	0
Media		26,2745
Mediana		24,0000
Modalità		24,00
Deviazione std.		6,65625
Varianza		44,306
Intervallo		42,00
Minimo		18,00
Massimo		60,00

Descriptive statistics: Gender

Indica il tuo genere

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Maschio	86	56,2	56,2	56,2
	Femmina	64	41,8	41,8	98,0
	Genere non-binario / Terzo genere	1	,7	,7	98,7
	Preferisco non dirlo	2	1,3	1,3	100,0
	Totale	153	100,0	100,0	



Factorial analysis: Mediator

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		,782
Test della sfericità di Bartlett	Appross. Chi-quadrato	605,383
	gl	3
	Sign.	<,001

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2,840	94,665	94,665	2,840	94,665	94,665
2	,092	3,082	97,746			
3	,068	2,254	100,000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1) Ho percepito lo scenario appena visualizzato come invadente	1,000	,942
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2) Ho percepito lo scenario appena visualizzato come intrusivo	1,000	,955
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3) Ho percepito lo scenario appena visualizzato come disturbante	1,000	,943

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1) Ho percepito lo scenario appena visualizzato come invadente	,970
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2) Ho percepito lo scenario appena visualizzato come intrusivo	,977
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3) Ho percepito lo scenario appena visualizzato come disturbante	,971

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Reliability analysis: Mediator

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
,971	,972	3

Factorial analysis: Dependent variable

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		,761
Test della sfericità di Bartlett	Appross. Chi-quadrato	595,539
	gl	3
	Sign.	<,001

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2,820	94,001	94,001	2,820	94,001	94,001
2	,127	4,237	98,238			
3	,053	1,762	100,000			

Metodo di estrazione: Analisi dei componenti principali.

Comunalità

	Iniziale	Estrazione
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1) Ho percepito lo scenario appena visualizzato come chiaro	1,000	,915
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2) Ho percepito lo scenario appena visualizzato come affidabile	1,000	,959
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3) Ho percepito lo scenario appena visualizzato come credibile	1,000	,946

Metodo di estrazione: Analisi dei componenti principali.

Matrice dei componenti[a]

	Componente 1
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1) Ho percepito lo scenario appena visualizzato come chiaro	,957
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2) Ho percepito lo scenario appena visualizzato come affidabile	,979
Indicare su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3) Ho percepito lo scenario appena visualizzato come credibile	,972

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

Reliability analysis: Dependent variable

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
,967	,968	3

One-Way ANOVA

Descrittive

DV

	N	Medio	Deviazione std.	Errore std.	95% di intervallo di confidenza per la media: Limite inferiore	95% di intervallo di confidenza per la media: Limite superiore	Minimo	Massimo
,00	78	2,1197	1,41928	,16070	1,7997	2,4397	1,00	6,00
1,00	75	5,6889	,78906	,09111	5,5073	5,8704	3,00	7,00
Totale	153	3,8693	2,12794	,17203	3,5294	4,2092	1,00	7,00

ANOVA

DV

	Somma dei quadrati	df	Media quadratica	F	Sig.
Tra gruppi	487,095	1	487,095	365,601	<,001
Entro i gruppi	201,179	151	1,332		
Totale	688,275	152			

Regression analysis: Model 4

```
Model  : 4
    Y  : DV
    X  : IV
    M  : MED

Sample
Size:  153

**************************************************************************
OUTCOME VARIABLE:
 MED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,8214      ,6747     1,3248   313,1269     1,0000   151,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,7650      ,1303    44,2352      ,0000     5,5075     6,0225
IV          -3,2938      ,1861   -17,6954      ,0000    -3,6616    -2,9261

**************************************************************************
OUTCOME VARIABLE:
 DV

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,9405      ,8845      ,5298   574,5538     2,0000   150,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6,6163      ,3079    21,4875      ,0000     6,0079     7,2248
IV           1,0000      ,2064     4,8456      ,0000      ,5922     1,4078
MED          -,7800      ,0515   -15,1566      ,0000     -,8817     -,6783
```

Main Test Questionnaire:

Please use this scale to answer the questions from 1 to 7:

1. Strongly disagree
2. Disagree
3. Somewhat disagree
4. Neither agree nor disagree
5. Somewhat agree
6. Agree
7. Strongly agree

Questions

I perceived the scenario as intrusive/invasive/disturbing.

I perceived the scenario as clear/reliable/credible.