INVESTIGATING THE FACTORS AFFECTING THE ACCEPTANCE OF GENERATIVE ARTIFICIAL INTELLIGENCE IN BUSINESS INTELLIGENCE APPLICATIONS

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Investigating the Factors Affecting the Acceptance

of Generative Artificial Intelligence in Business Intelligence Applications

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DECLARATION OF ORIGINALITY

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ABSTRACT

Investigating the Factors Affecting the Acceptance of Generative Artificial Intelligence in Business Intelligence Applications

Based on previous technology acceptance and adoption literature, this research aims to understand and empirically test the critical factors for generative AI acceptance in business intelligence applications. Artificially Intelligent Device Use Acceptance and Task-Oriented Artificial Intelligence Acceptance models were used as theoretical foundations to interpret users' acceptance when interacting with generative AI services in business intelligence applications. For data collection, an online survey was developed by adapting validated measurement scales from other AI adoption literature. According to the survey results, data were collected from 149 participants. The effects on the extent of acceptance were experimentally tested using the PLS-SEM analysis. The results showed that utilitarian motivation, continuous improvement, conversational intelligence, perceived usefulness, flow experience, trait curiosity, and trust played significant roles in the acceptance of generative AI technology. However, there was no support for the influence of task-technology fit and performance risk factors. Considering the rapid development of AI technologies, developing and empirically testing an adoption model will guide researchers, technology providers, and users to adopt and use this technology successfully.

ÖZET

İş Zekası Uygulamalarında Üretken Yapay Zekanın Benimsenmesini Etkileyen Faktörlerin Araştırılması

Önceki teknoloji kabul ve benimseme literatürüne dayanarak, bu araştırma iş zekası uygulamalarında üretken AI benimsemesi için kritik faktörleri anlamak ve deneysel olarak test etmeyi amaçlamaktadır. İlk olarak, iş zekası uygulamalarında üretken AI hizmetleriyle etkileşim kurarken kullanıcıların kabulünü yorumlamak için Yapay Zekalı Cihaz Kullanım Kabulü ve Görev Odaklı Yapay Zeka Kabulü modelleri teorik temeller olarak kullanıldı. Ardından, diğer yapay zeka benimseme literatüründen doğrulanmış ölçekler uyarlanarak çevrimiçi bir anket geliştirildi. Anket sonuçlarına göre, 149 katılımcıdan veri toplandı. Bu veriler kullanılarak, benimsemenin kapsamı üzerindeki etkiler PLS-SEM metodolojisi kullanılarak deneysel olarak test edildi. Sonuçlar, faydacı motivasyon, sürekli iyileştirme, konuşma zekası, algılanan yararlılık, akış deneyimi, özellik merakı ve güvenin üretken yapay zeka teknolojisinin kabulünde önemli roller oynadığını gösterdi. Ancak, görev teknoloji uyumu ve performans risk faktörlerinin etkisine dair bir destek bulunamamıştır. Yapay zeka teknolojilerinin hızlı gelişimini göz önünde bulundurarak, bir benimseme modeli geliştirmenin ve deneysel olarak test edilmesi araştırmacılara, teknoloji sağlayıcılarına ve kullanıcılara bu teknolojiyi başarılı bir şekilde benimsemeleri ve kullanmaları konusunda rehberlik edecektir.

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DEDICATION

To my family

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

AI	Artificial Intelligence
AIDUA	Artificial Intelligence Device Usage Acceptance
BI	Business Intelligence
DL	Deep Learning
DOI	Diffusion of Innovation Theory
DSS	Decision Support System
DWH	Data warehouse
EIS	Executive Information Systems
ESS	Executive Support Systems
ETL	Extract, Transform, Load
GANs	Generative Adversarial Networks
GenAI	Generative Artificial Intelligence
GPTs	Generative Pretrained Transformers
IT	Information Technology
KPIs	Key Performance Indicators
LLMs	Large Language Models
LSTM	Long Short-term Memory
LV	Latent Variable
MIS	Management Information System
ML	Machine Learning

NLP	Natural Language Processing
OLAP	Online Analytical Processing
RNNs	Recurrent Neural Networks
T-AIA	Task-Oriented Artificial Intelligence Acceptance
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TPS	Transaction Processing Systems
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
VAEs	Variational Autoencoders

CHAPTER 1

INTRODUCTION

Organizations rely heavily on data, and due to the volume and speed of data generation, data has become the fuel that affects these organizations (Hazboun, Owda, & Owda, 2021). One of the systems that enables organizations to use their data effectively is business intelligence (BI) applications. A BI system can quickly distinguish fact-based concerns and their relationships in business operations, encouraging businesses to respond with actionable actions to achieve their goals (Chen & Lin, 2021).

The developments in AI changed the traditional BI, which emerged in the 1960s and was considered a simple system that only helped share information between businesses (Afsaruddin, Agrawal, & Nayak, 2023). Increasing the capacity of predictive analysis (Afsaruddin et al., 2023), generation of synthetic data (Bharathi, Subin, Hariharan, Balaji, & Balaji, 2024), customer clustering (Hamzehi & Hosseini, 2022), churn prediction (Afsaruddin et al., 2023), and sentiment analysis (Gholami, Zarafshan, Sheikh, & Sana, 2023) are examples of the increasing capabilities of BI thanks to the advances in AI. In addition, the capabilities of BI continue to grow with the development of generative artificial intelligence (genAI) technology. Since ChatGPT, the most popular form of genAI, was publicly announced by OpenAI on November 30, 2022, it has begun to attract the attention of all interested parties, including businesses, consumers, regulators, and public policy leaders (Shankar, 2024). Unlike other types of AI, genAI is defined and often distinguished by its ability to generate new content that is non-trivial, anthropomorphic, precise, and appears to be meaningful (Silva, Kaynak, El-Ayoubi, Mills, Alakhakoon, & Minas, 2024). The emergence of GenAI has proclaimed a new phase in technology, offering groundbreaking capabilities to generate more from simple prompts, text, images, and code (Ghimire & Edwards, 2024). After these developments, BI vendors have begun to integrate genAI into their applications. For example, in IBM's genAI-powered BI vision, it was stated that genAI-powered BI by IBM Granite foundational models is prepared to transform the future of BI (Andrade, 2024). Another BI vendor, Microstrategy, shared that with the transformative change that comes with genAI, organizations are expected to create intuitive interfaces by utilizing the power of AI, making data-driven decision-making more efficient and accessible than ever (Ires, 2024). Arjunan and Umamageswari (2024) stated that genAI is a significant force in BI processes that improves data generation, enhances predictive modeling, automates reporting, facilitates decision making, and optimizes diverse organizational processes. Additionally, the ability to synthesize data, customize users' experiences, and simplify processes through genAI demonstrates its comprehensive impact on BI (Arjunan & Umamageswari, 2024). GenAI can extract large amounts of unstructured data and organize it efficiently and appropriately (Kshetri, Rojas-Torres, Hanafi, Al-Kfairy, O'Keefe, & Feeney, 2024), and GenAI tools can help obtain descriptive statistics and detect trends and outliers (Kshetri et al., 2024).

1.1 Research objectives

As Desai and Desai (2025) state, the successful integration of GenAI into BI processes is based on the mutual relationship between people, processes, and technology. The primary objective of this research study is to develop a model to effectively evaluate users' acceptance of genAI technology in BI applications.

Although major BI vendors have begun to integrate GenAI, the number of studies on GenAI integration in BI in the academic literature is limited, as Desai and Desai (2025) stated. Additionally, to the best of our knowledge, there is no academic study on genAI acceptance in BI. Integrating genAI into organizational environments accelerates technological and strategic changes, while also requiring a theoretical reassessment in the fields of information systems and strategic management (Al-kfairy, 2025). In this sense, there is a gap in the literature. Therefore, the aim of this study is to find the factors affecting the acceptance of genAI in BI applications by revealing the factors affecting the acceptance of AI technology by users and to contribute to the successful execution of this process by organizations. In line with this primary goal, this study aims to develop a framework based on the Artificial Intelligence Device Usage Acceptance (AIDUA) and Task-Oriented Artificial Intelligence Acceptance (T-AIA).

In line with the objectives sought to be achieved in this study, the research questions were formulated as follows:

i. What is the status of acceptance of AI technology in the current literature?
ii. What factors affect users' willingness to accept genAI technology in BI applications?

1.2 Outline of thesis

This study evaluates the key factors that play a role in the acceptance of genAI technology in BI processes. Chapter 1 presents a general introduction to this study, the motivation for the study, and the research questions. Chapter 2 presents existing literature on BI applications, genAI technology, and the Technology Acceptance Model, which will support the development of this study. Chapter 3 presents hypotheses based on the literature review and proposes a model that fits users' perceptions about acceptance of genAI-supported BI technology. Chapter 4 provides survey structure, data collection, and data cleaning phases to evaluate the study’s hypotheses. Chapter 5 presents the survey results and supported and unsupported model structures. Chapter 6 provides more detailed discussiıns and evaluations of the study's results. In addition, Chapter 6 presents the study's contributions to the literature, practical implications, limitations of the study, and valuable insights for future studies based on this study.

CHAPTER 2

LITERATURE REVIEW

The literature review was intended to evaluate the importance of the research topic and the key elements of the research questions, as well as to analyze other acceptance and adoption studies to examine genAI acceptance. For this purpose, this section includes a literature review conducted in three subcategories related to genAI acceptance in BI. The first section discusses the definition, history, components, tools used, trends, and impact on organizational performance of BI. The second section defines genAI while explaining the history, types of models, use cases, and implications for organizational performance and challenges of genAI. The last section continues with a theoretical foundation of technology adoption and acceptance models. It presents the theories used in our conceptual research model, examining both an ideal conceptual research model and a model to be researched based on the literature review.

2.1 Business intelligence (BI)

Developments in technology are accelerating day by day and entering our lives very quickly. This speed and impact of developments pave the way for the production of large volumes of data. According to the Statista Report, global data volume is expected to increase by more than 394 terabytes by 2028, as seen in Figure 1 (Statista Report, 2024). Extracting meaningful insights from this enormous amount of data and using it for strategic decision-making is more complex than ever. Therefore, it is becoming increasingly important for companies to extract information from data and use it effectively. In the current environment, BI is essential to create a strategy and conduct data-driven operations (Afsaruddin et al., 2023).

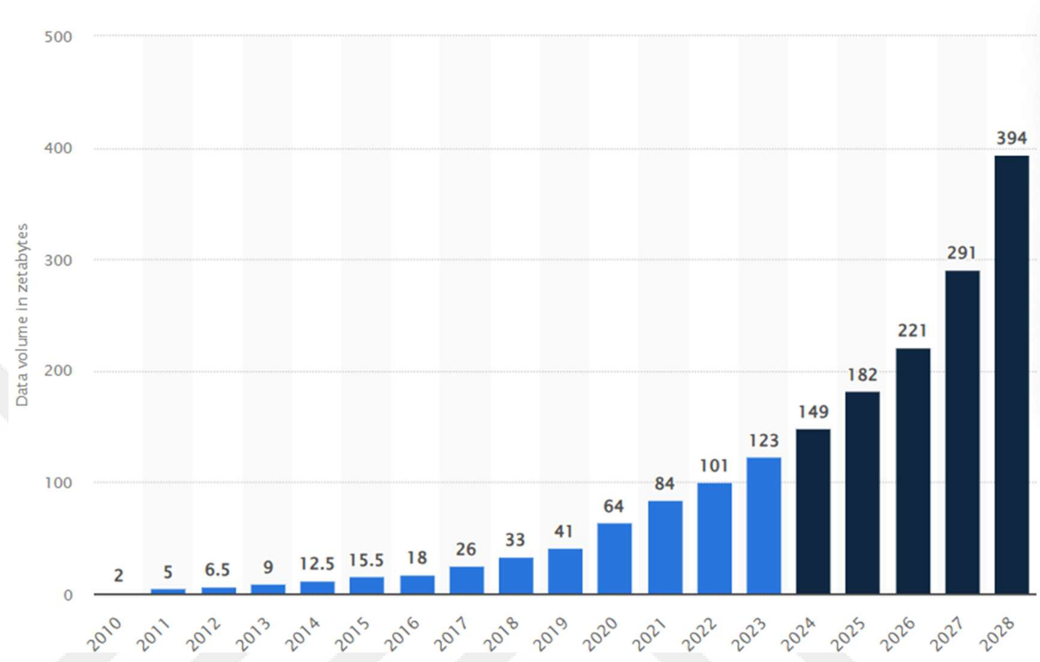

Figure 1. The growth of data
Source: Statista, 2024 (Adapted)

BI defines methods, approaches, and ideas that expand the support of fact-based systems that positively contribute to a company's decision-making processes (Afsaruddin et al., 2023). In addition, BI refers to the infrastructure that hardware and software vendors and information technology consultants use to store, integrate, and then report and analyze data from the business environment (Laudon & Laudon, 2014). The primary purpose of the services provided by BI is to identify decision-making errors by analyzing past performance and to predict and forecast future needs, advantages, and the most appropriate course of action based on the company's data (Gurcan, Ayaz, Dalveren, & Derawi, 2023). It is vital for many companies, as information is one of the most valuable assets of companies and one of the primary resources for their growth (Romero, Ortiz, Khalaf, & Prado, 2021). Advanced BI tools can derive information from raw data and strategy from analytical insights (Alqhatani, Ashraf, Ferzund, Shaf, Abosaq, Rahman, Irfan, & Alqhtani, 2022) and increase the efficiency and competitiveness of the organization (Guarda, Carvaca, Gozabay, & Saquicela, 2022). Tools, database design, data warehouses, performance management, and techniques are included in the broad category of BI (Gholami et al., 2023).

2.1.1 History of business intelligence

This section explains BI's historical background based on the relevant literature. Figure 2 presents a summary timeline with the major milestones to present the historical development in a more systematic way.

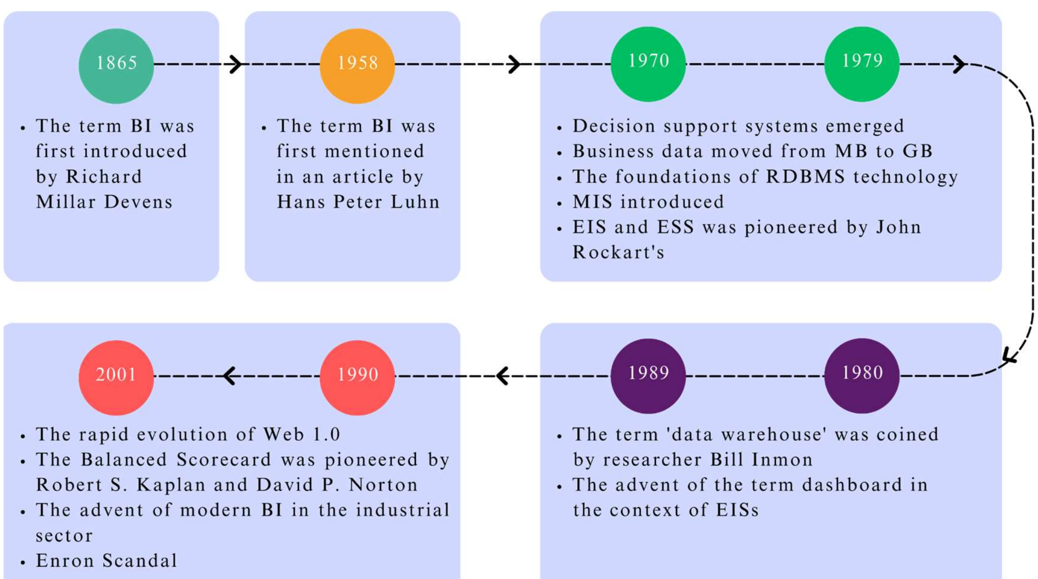

Figure 2. Key milestones in BI history
Source: Drawn by the author

In 1865, the term BI, which is considered the foundation of the corporate system and innovative business, was initially introduced by Richard Millar Devens in Cyclopedia of Commercial and Business Anecdotes (Sinha, Panwar, Gupta, & Bhatnagar, 2022). The aim is to demonstrate how Sir Henry Furnese made a massive profit by collecting information in a banking application and processing it in this information system (Sinha et al., 2022). This study shows the importance of making strategic decisions based on data rather than being intuitive. However, almost 100 years later, the term BI was first mentioned in an article by Hans Peter Luhn, who is a IBM researcher, in 1958 and was used to refer to the ability to explore facts proposed in a way that can be used to reach a goal (Hamzehi & Hosseini, 2022). In this article, Luhn defined the term BI with two components as business and intelligent systems (Tutunea & Rus, 2021).

The 1960s and 1970s were the time when the first technological foundations of BI were laid. After Luhn's paper, BI became popular, and many researchers started to work on it. These studies invented the decision support system (DSS) (Sinha et al., 2022). With the invention of decision support systems and their integration into BI, the impact of BI quickly increased in business life. It has been argued that BI is based on DSS, which emerged in the early 1970s, when managers used computer applications to represent organizational decisions (Olszak, 2016). Decision support systems' development continued rapidly from the 1960s to the mid-1980s (Hamzehi & Hosseini, 2022).

In the 1970s and 1980s, business data moved from megabytes to gigabytes, presenting the challenge of "big data" for the first time (Hu, Wen, Chua, & Li, 2014, p.4). However, during this period, there was an urgent need to store data and run relational queries for business analysis and reporting (Hu et al., 2014). Research was conducted to create a "database machine" with integrated hardware and software to solve the existing problems (Hu et al., 2014). In the early 1970s, the foundations of the revolutionary relational database technology were laid with the work of E.F. Codd at the IBM San Jose Research Laboratory (Wade & Chamberlin, 2012). In the late 1970s, the management information system (MIS) was introduced as the first DSS (Sinha et al., 2022). Middle managers used MIS to support decision-making, mostly using a group of regular production reports based on data extracted and summarized from the company's core transaction processing systems (TPS) (Laudon & Laudon, 2014). Furthermore, in 1979, the development of Executive Information Systems (EIS) and Executive Support Systems (ESS) was pioneered by John Rockart's research (Zhengmeng & Haoxiang, 2011). The primary purpose of EIS was to display a set of key financial metrics using a simple interface that even a manager could understand (Few, 2006). These developments have contributed significantly to the evolution of the BI landscape. Today, the BI environment consists of data from different sources, BI infrastructure, a BI toolkit, administrative users and methods, BI delivery platforms such as MIS, DSS, or ESS, and the user interface (Laudon & Laudon, 2014).

The 1980s witnessed the early days of the Digital Revolution, also known as the Third Industrial Revolution, which marked the beginning of a paradigm shift in technological advancement, moving analog electronic and mechanical devices into the realm of machine learning (ML) and artificial intelligence (AI) (Taori & Dasararaju, 2019). By the late 1980s, the proliferation of digital technology had led to data volumes reaching terabytes, thereby exceeding the storage and/or processing capacity of a single comprehensive computer system (Hu et al., 2014). The term data warehouse was coined by researcher Bill Inmon following his involvement in inhouse data analysis during the 1980s (Sinha et al., 2022). The concept of a data warehouse (DWH) emerged with the intention of consolidating historical, integrated, and aggregated data into a centralized repository to support knowledge workers (Gils, 2023). The development of technologies such as DSS, EIS, Data Warehousing, OLAP, and Data Mining has substantially impacted BI's evolution (Tutunea & Rus, 2021). In the late 1980s, these systems evolved significantly, leading to their recognition as BI (Zwingmann, 2022). Concurrently, the 1980s also mark the advent of the term dashboard in the context of EISs (Few, 2006).

During the 1990s, the advent of data warehousing, online analytical processing (OLAP), and subsequently, BI, precipitated a concerted response aimed at maintaining pace with the rapid advancements characteristic of the information age (Few, 2006). Towards the end of the 1990s, the rapid evolution of Web 1.0 ushered in the Internet age, accompanied by the emergence of substantial semi-structured or unstructured web pages, capable of housing terabytes or petabytes (PB) of data (Hu et al., 2014). The advent of the Internet and the exponential surge in data volume have rendered BI an indispensable tool. The Balanced Scorecard, a novel management approach pioneered by Robert S. Kaplan and David P. Norton, led to the conceptualisation and utilisation of key performance indicators (KPIs) (Few, 2006). Initially unpopular in the early 1990s, these indicators gained prominence in the late 1990s (Few, 2006). The balanced scorecard technique was developed to focus on long-term success by incorporating non-financial strategic measures and financials (Mittal & Sinha, 2023). As can be seen in Figure 3, the scorecard includes four different perspectives: financial, internal business, innovation and learning, and customer perspective. In this way, the disparate elements of a company’s competitive agenda, such as being customer-focused, reducing response time, enhancing quality, emphasizing teamwork, shortening new product launch times, and long-term management, are brought together in a single management report (Kaplan & Norton, 1992). Over time, these developments have reinforced the demand for BI. However, it was not until the 1990s that BI gained popularity in business and IT (Chen, Chiang, & Storey, 2012). The advent of modern BI in the industrial sector can be traced back to the early 1990s, a development that emerged in direct response to the demands of managers for effective and efficient enterprise data analysis (Golfarelli, Rizzi, & Cella, 2004). The primary objective of this development was to enhance decision-making processes and to facilitate a more profound comprehension of the status of their respective companies.

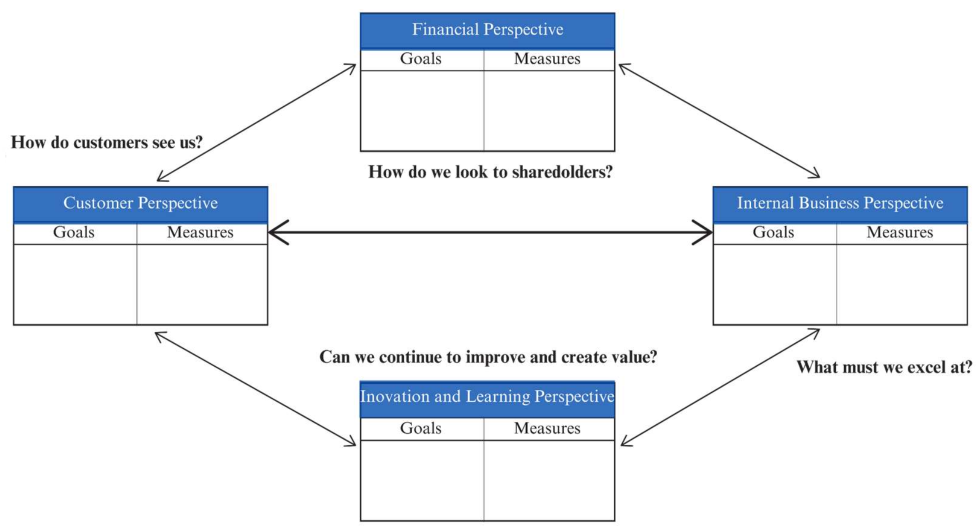

Figure 3. Overview of scorecard
Source: Mittal & Sinha, 2023 (Adapted and redrawn by author)

Before the first decade of the 21st century, BI was utilised exclusively by prominent and wealthy companies (Sakys & Butleris, 2011). However, following this period, a discernible trend emerged, and it began to be adopted by small and medium-sized businesses and organisations (Sakys & Butleris, 2011). It was during this period that the significance of dashboards became evident. The Enron scandal of

2001 brought to the fore the realisation that dashboards were much more than an emerging technology (Few, 2006). Instead of establishing a functional internal audit mechanism, Enron ignored questionable accounting practices and fraudulent financial reporting by relying on external audit support to perform the internal audit function (Cuong, 2011). In the aftermath of the Enron scandal, numerous BI vendors entered the market, including those who had not previously offered dashboard products (Few, 2006). These vendors did so by strategically renaming existing products, creating bundled offerings, or swiftly acquiring the rights to products held by smaller vendors (Few, 2006).

Considering the historical processes mentioned above, BI can be divided into three distinct eras as seen in Figure 4: BI 1.0 (IT Generated BI), BI 2.0 (Business Generated BI), and BI 3.0 (Machine Generated BI) (Alghamdi & Al-Baity, 2022; Antunes, Cardoso, & Barateiro, 2021; Ereth & Eckerson, 2018).

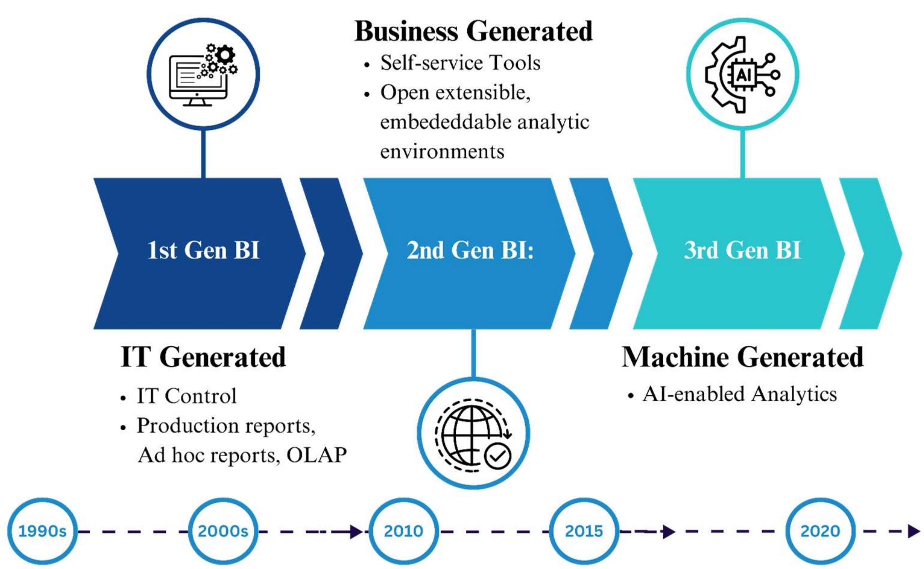

Figure 4. Evolution of BI
Source: Ereth & Eckerson, 2018 (Adapted and redrawn by author)

First Generation of BI (IT Generated): The initial phase of BI was characterised by the emergence of Enterprise Data Warehouses (EDW), management information systems, executive information systems, and decision support systems, which were OLAP-based solutions (Alghamdi & Al-Baity, 2022). Statistical methods formulated in the 1970s and data mining techniques introduced in the 1980s form the basis of analytical techniques widely used in this generation, which gained popularity in the 1990s (Chen, Chiang, & Storey, 2012). The core objective during this period was on the collection, enhancement, integration, storage, and ensuing access of information, intending to sustain its accuracy, timeliness, and practical utility (Few, 2006). In the initial phase, designated as traditional BI, reporting processes were carried out with the help of technical experts. Since users were dependent on technical experts, they had to act according to the technical experts' plans and could request predefined reports.

Second Generation of BI (Business Generated): The advent of Big Data can be traced back to the 2000s, coinciding with the emergence of Web 2.0 and the widespread adoption of Google and social media platforms such as Facebook (Kumar, Marchena, Awalla, Li, & Abdalla, 2024). The 2000s witnessed the emergence of web intelligence, web analytics, and user-generated content obtained from Web 2.0-based social and crowdsourcing systems, thereby ushering in the BI&A 2.0 era (Chen, Chiang, & Storey, 2012). This era focused on text and web analytics for unstructured web content. The integration of web technologies has led to a proliferation of unstructured data that exceeds the capacity of conventional databases to manage effectively (Kumar et al., 2024). Furthermore, the BI 2.0 generation is characterised by the concept of self-service BI. It enables the comprehensive evaluation of data by business users, enabling the derivation of insights through the application of advanced data discovery tools and the enhancement of decision-making processes, thus eliminating the need for assistance from the IT department (Prat, 2019). During this period, visualization tools with user-friendly interfaces came to the fore. Thanks to self-service BI, users produce reports and analyses without depending on IT departments, reducing their dependency on technical users. As a result, users became faster and more independent in data-driven decision-making processes.

Third Generation of BI (Machine Generated): AI-powered analytics is gaining importance in the third generation of BI, which started in 2015 (Prat, 2019). In this generation, BI has been transformed with the implementation of AI and augmented analytics functions (Alghamdi & Al-Baity, 2022). AI has enabled BI users to make decisions based on future predictions and forecasts rather than just reporting historical data. Techniques such as ML, DL, and NLP have enabled BI users to gain advanced insights during this period.

2.1.2 Traditional BI architecture

Traditional BI systems utilize reporting systems to reach transactional data stored in the data warehouse to support organizational decisions (Vo, Thomas, Cho, De, & Choi, 2018). The ideal approach in organizational BI architectures is divided into back-end architecture, which is related to data collection and data organization, and the front-end architecture, which is related to analytics and data visualization for the user (Vo et al., 2018). The back-end of the architecture consists of a data integration pipeline that extracts data from different operational sources and then loads it into the data warehouse, cleansing, integrating, and transforming it (Dayal, Castellanos, Simitsis, & Wilkinson, 2009). Traditional BI practically consists of a three-layered conceptual architecture as seen in Figure 5. In the pre-cloud era, this architecture was the only option, since resources were expensive and scarce, the three stages-extract, transform, and load-were run together as a pipeline, and a failure in one would affect the other processes (Simitsis, Skiadopoulos, & Vassiliadis, 2023).

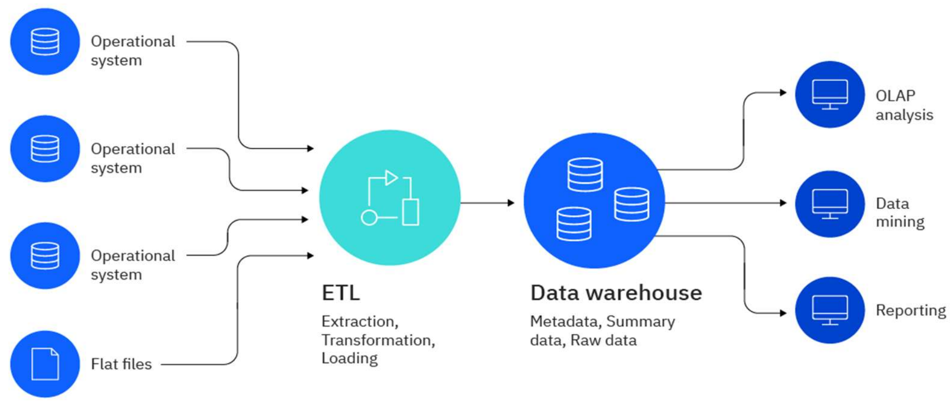

Figure 5. Traditional BI architecture
Source: Holdsworth & Kosinski, 2024 (Adapted)

2.1.3 Components of business intelligence

A comprehensive BI enterprise system can include the entire spectrum of a BI process, consisting of key elements such as data management and integration, analysis, presentation, delivery, and domain applications that include all components (Zheng, Zhang, & Li, 2014).

2.1.3.1 Data Management and Integration

Data sources are the starting point of BI architecture. An organization's data sources can consist of internal activities or external sources. Internal data refers to data generated by systems and employees within organizations, while external data refers to information from various sources outside the organization, such as articles, patents, books, and analytical reports (Barbieri, Laserna, & Mateus, 2024). These internal and external data sources can diversify with technological developments. For example, analyzing customer comments has become very important for companies due to social media. These developments have created the need to use data from different sources. Performance measurement, strategy development, productivity increase, and strategic planning can be achieved using data from many sources (Vo et al., 2018). Therefore, data management is essential for effectively using data from different sources in BI.

Data from different sources is brought together for BI processes in the data integration phase. Databases, data warehouses, data models, and ETL (extract, transform, and load) are popular technologies and techniques in data management and integration processes (Zheng, Zhang, & Li, 2014). ETL pipelines are used to extract actions and events from operational databases and then load them into the enterprise data warehouse (Dayal et al., 2009). After these processes, the data is cleaned, transformed, and standardized, ready to be stored in a data warehouse.

2.1.3.2 Data Analysis

Data Analysis enables the extraction of useful information from data stored in the data warehouse by applying computer-based methodologies (Barbieri, Laserna, & Mateus, 2024). Data collected from different sources is processed in the data analysis phase and then reported. SQL queries, AI, and statistics can be used for analysis purposes, and insights can be strengthened.

As indicated in Figure 6, four basic analysis methods are used in data analysis processes: descriptive, diagnostic, predictive, and prescriptive. The primary purpose of every BI or reporting infrastructure is to perform descriptive and diagnostic analyses using historical data and to provide retrospective views and insights

(Zwingmann, 2022). However, developments in AI technologies have enabled predictive and descriptive analyses in BI processes.

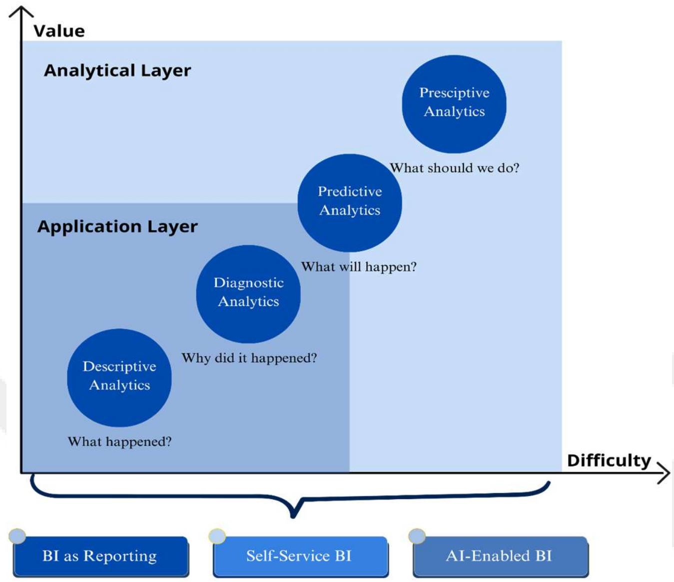

Figure 6. Data analysis stages
Sources: Ereth & Eckerson, 2018; Zwingmann, 2022 (Adapted and redrawn by author)

Descriptive Analytics: To understand the processes in the organization and see the underlying trends and behaviors, it is necessary first to reach a solid BI analysis (Nakhal, Patriarca, Antonioni, & Paltrinieri, 2021). The descriptive analysis method extracts meaningful information from historical data and provides decision-makers with an overall view of business performance, trends, and patterns. Users can understand their processes by making sense of current data using descriptive analytics. It is one of the basic and common analysis methods for BI.

Diagnostic Analytics: Diagnostic analysis uses historical data to understand the causes of events and trends. Unlike descriptive analysis, it is essential to comprehend the factors behind events and trends. Diagnostic analysis can identify potential business risks, improvement opportunities, and areas requiring further research (Igulu, Osuigbo, & Singh, 2023).

Predictive Analytics: Predictive analysis is an analysis method that uses past data to predict future events. It requires the use of more advanced methods than diagnostic and descriptive analytics. Predictive analytics uses advanced algorithms and data science techniques to analyze data and predict future events (Igulu, Osuigbo, & Singh, 2023). Methods such as ML, deep learning (DL), statistical techniques, and data mining can be used for predictive analysis. Using data mining techniques helps manage the volume and diversity of data and enables proactive, information-driven decisions to be made and BI processes to be improved (Vo et al., 2018). Predictive analytics enables optimizing marketing campaigns by analyzing customer reviews, acquiring new customers, reducing customer churn rates, detecting fraud, creating new business models, and increasing operational efficiency (Gupta & Kumar, 2024).

Prescriptive Analytics: Predictive analytics, as an enhanced form of data analytics and BI, recommends specific actions organizations can take to improve their operational process and reach targeted goals using data-driven insights and predictive analysis (Igulu, Osuigbo, & Singh, 2023). Prescriptive analytics is considered the most advanced stage of advanced analytics methods. It interprets existing data, such as diagnostic and descriptive analytics, or predicts future results, such as predictive analysis, and suggests what actions users should take. Prescriptive analytics attempts to find the optimal course of action for a given business problem using a variety of approaches, including optimization, simulation, decision analysis, and ML (Alkhaldi, 2023). It is essential for businesses to increase operational efficiency, reduce risks, and achieve strategic goals.

2.1.3.3 Presentation

BI technology enables reliable and efficient decision-making processes by allowing users to develop dynamic reports on various information sources by integrating different data sources (Rahman, Mahmud, Zahari, Zukarnain, & Putra, 2024). With data visualization using BI tools, complex data sets can be transformed into easily understandable and insightful representations (El-khalili, Arqoub, Hasan, Banna, & Arafah, 2024). Various presentation methods, such as reports, dashboards, scorecards, etc., can be adopted (Barbieri, Laserna, & Mateus, 2024). Presentation enables users to present complex data through understandable graphs, tables, and interactive dashboards.

Visualizations allow users to quickly identify trends, patterns, and outliers in large volumes of complex data and make fast and effective decisions. In particular, tools such as graphs, tables, maps, and interactive dashboards make complex and multi-dimensional data understandable and help users see critical information and relationships in the data. A visualization should be simple to interpret without clarification, and to do this, the dashboard should contain only important text, such as chart titles, category labels, or data values (Pappas & Whitman, 2011).

2.1.3.4 Delivery

Delivery provides users with access to outputs from data, reports, and various tools for analysis and reporting. In the delivery process of BI, data is collected, processed, and analyzed. For the management and efficient delivery of the BI platform, assets such as dashboards, application servers, BI servers, and web servers allow users to manage and use other components of their BI environment (Sinha et al., 2022). Standard delivery methods include mobile applications, personal office programs such as Excel, and BI online portals (Zheng, Zhang, & Li, 2014). Thus, users can easily understand the information. The delivery process in BI is essential for making strategic and quick decisions.

For example, a dashboard is a tool that visually brings together and organizes important information on a single screen, allowing the user to see the most essential information at a glance to achieve their goal (Few, 2006). As indicated in Table 1, Pappas and Whitman (2011) identified three roles: strategic, operational, and analytical. Dashboards in the strategic category are long-term, will be used more in the decision-making or inquiry phase after the data is examined, and are less interactive. Dashboards in the operational category are used for instant and immediate decision making and are at a medium level of interaction. Dashboards in the analytical category are used for exploring what-if scenarios and are a category with a high level of interaction.

Table 1. Overview of Dashboard Categories

Source: Pappas & Whitman, 2011 (Adapted)

Category	Purpose	Timeframe	Data Scope	Update Frequency	Interactivity
Strategic	See and decide, or question	Months/ Years	Enterprise-wide, Cross-business unit	Moderate	Low
Operational	See and act	Minutes/ Days	Business unit specific	High	Moderate
Analytical	See and question, explore what-if scenarios	Minutes to Years	Enterprise-wide, Cross-business unit, or isolated	Low	High

2.1.3.5 Domain Application

The domain application component emphasizes the analysis and reporting capabilities specific to a particular sector or business purpose in BI processes. These applications are usually designed for sector-specific purposes and data standards. Because the methods and metrics used in BI processes may not be suitable for every sector, it is necessary to understand sectoral needs and progress towards the target. In this way, BI processes can be supported in a way that is appropriate for the purpose instead of more general methods, and the required information can be reached more quickly and effectively. For example, in the healthcare sector, it is necessary to know the KPIs specific to healthcare enterprises, their meaning and definition, how they are measured and used, and what kind of decisions they support (Zheng, Zhang, & Li, 2014). The main advantage of such applications is that they allow institutions to effectively monitor KPIs directly in their fields.

2.1.4 Business intelligence tools

BI tools are software applications that allow organizations to rely on data-driven decisions by collecting, analyzing, and visualizing data (Vaish, Shrivastava, & Sen, 2020). These tools are necessary to construct a strategic approach and manage data-driven operations (Afsaruddin et al., 2023).

The emergence of BI as a software category for supporting business decision-making in the 1980s caused significant growth in the market for BI software tools and features (Singh & Nayeem, 2011). Today, vendors have developed many BI tools to understand and visualize data and support organizational decision-making.

Determining BI tools that are highly effective and can create a significant impact in organizations is a difficult task for business managers (Romero et al., 2021). There are six leading BI vendors in Gartner's Magic Quadrant: Microsoft, Salesforce, Google, Oracle, Qlik, ThoughtSpot (Gartner, 2024). In addition to leading vendors, Table 2 shares IT-enabled or AI-enabled analytics and BI platforms provided by Gartner.

Table 2. Overview of BI Vendors and Their Products

Source: Gartner, nd (Compiled by author)

Vendors	Products
Salesforce	Tableau, CRM Analytics
Tableau	Open Source
Microsoft	Power BI, SQL Server Reporting Services, Azure Data Explorer, Microsoft Fabric
Qlik	Qlik Sense QlikView
SAP	SAP BusinessObjects BI Suite, SAP Analytics Cloud, SAP Crystal Reports
Sisense	Sisense Fusion Analytics, Sisense Fusion Embed
Oracle	Analytics Cloud, Analytics Server, Fusion Data Intelligence, Big Data Discovery, Big Data Discovery Cloud Service
MicroStrategy	MicroStrategy
AWS	Amazon QuickSight
SAS	SAS Enterprise Guide, SAS Office Analytics, SAS Visual Analytics, SAS Viya
Spotfire	Spotfire
Domo	Domo Data Experience Platform
IBM	IBM Cognos Analytics
ThoughtSpot	Mode Platform
Zoho	Zoho Analytics, Zoho DataPrep
Pyramid	Pyramid Decision Intelligence Platform, Pyramid BI Office
insightsoftware	Logi Symphony, Zoomdata, Exago BI, DecisionPoint For Excel, Izenda BI Platform, Logi Vision, DecisionPoint Enterprise, Jreport, Logi Analytics
Infor	Birst
Dimensional Insight	Diver Platform
Board International	Board
Incorta	Incorta Unified Data and Analytics Platform
Yellowfin	Yellowfin
GoodData	GoodData Platform
Alibaba	Alibaba Quick BI
Databricks	Databricks Data Intelligence Platform
Ibi	ibi WebFOCUS
Sigma	Sigma
Jaspersoft	Jaspersoft
Alteryx	Alteryx AI Platform for Enterprise Analytics
Cisco Systems	Splunk Cloud

2.1.5 Overview of emerging trends in business intelligence

Technological developments also create new development areas for BI. While traditional BI can only perform descriptive analysis on existing data, these analyses are not starting to meet the demand due to the increasing data volume and production speed. For this reason, BI is also evolving according to accelerating technological developments and increasing user needs. While BI trends are changing the business landscape by being affected by the latest developments in technology, it seems that they are also being influenced by the rapidly developing AI. Due to advances in AI technologies, the intensity level of BI predictive analysis has increased significantly, providing significant advantages such as high efficiency, high accuracy, time saving, and resource saving (Afsaruddin et al., 2023). Technological advances in the field of AI have the capacity to increase the chances of organizations to integrate knowledge gained from AI and its subfields into a more comprehensive business plan (Zhao & Zhang, 2024). AI-powered BI will not only simplify and democratize data accessibility and analysis but will also transform BI by providing access to information enriched with deeper insights (Fulara, 2024). AI-powered BI solutions automate data processing, identify hidden patterns, and predict future outcomes more accurately. Many large organizations are still in the second phase of BI (Zwingmann, 2022). Rapid developments in AI hold great potential for companies to be explored. These developments, such as ML, DL, Natural Language Processing (NLP), and genAI, have revealed different potentials in the use of AI in BI. The general hierarchy and relationships between these concepts are shown in Figure 7.

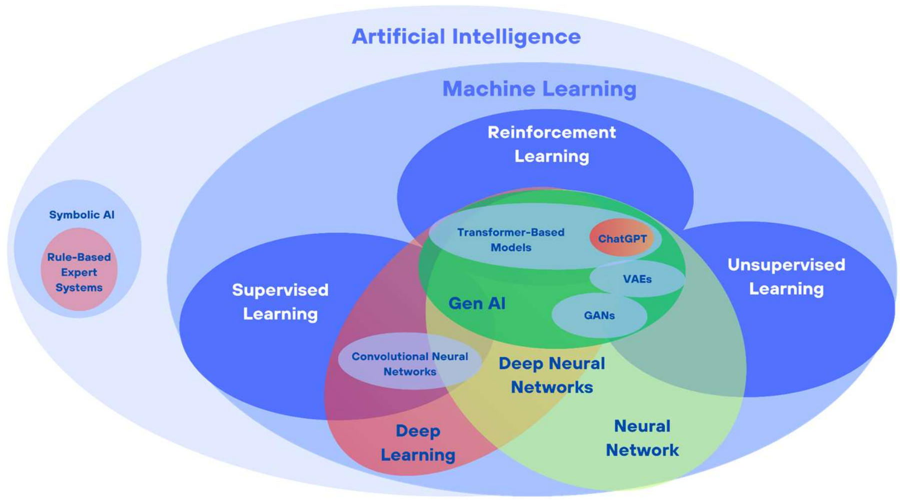

Figure 7. Overview of AI technologies
Source: Winter, nd (Adapted and redrawn by the author)

Integrating AI and ML into traditional BI systems is one prominent trend. ML is a type of AI that uses statistical techniques to enable machines to make predictions or decisions by learning from data without explicit programming or commands (French & Shim, 2024). Due to the large amount of data produced, using ML techniques in BI processes from data has become indispensable in strategic decision-making (Madhuri, 2019). ML can be used in BI processes for purposes such as customer churn prediction (Afsaruddin et al., 2023; Pustokhina, Pustokhin, Aswathy, Jayasankar, Jeyalakshmi, Díaz, & Shankar, 2021), demand forecasting (Khan et al., 2020), price prediction (Mahoto, Iftikhar, Shaikh, Asiri, Alghamdi, & Rajab, 2021), production prediction (Primawati, Sitanggang, Annisa, & Astuti, 2024), customer clustering (Alqhatani et al., 2022; Hamzehi & Hosseini, 2022; Rachman, Santoso, & Djajadi, 2021), sentiment analysis (Madhuri, 2019; Srinivasan, Shah, & Surendra, 2021; Sreesurya, Rathi, Jain, & Jain, 2020), credit risk assessment (Biswas, Mondal, Kusumastuti, Saha, & Mondal, 2022) and detection of fraud, corruption, non compliance (Caruso, Bruccoleri, Pietrosi, & Scaccianoce, 2023). Predictive analytics, enabled by ML, enables organizations to forecast market trends, customer behavior, and risk factors, allowing them to respond in advance rather than reactively refine strategies. Augmented data management leads to hyper-automation of data workflows through augmented analytics and automation with AutoML, while advanced analytics and data storytelling enable deeper insights and more effective identification of findings (Kumar et al., 2024).

As an essential part of AI, NLP creates intelligent models by simulating human thinking (Hazboun, Owda, & Owda, 2021). The use of NLP in BI processes enables the identification, understanding, and creation of texts, supports the creation of queries and dashboards, and enables the generation of recommendations. NLP allows BI to recommend generation (Guessoum, Djiroun, Boukhalfa, & Benkhelifa, 2022), conversation generation (Quamar, Ozcan, Miller, Moore, Niehus, & Kreulen, 2020), query generation (Hazboun, Owda, & Owda, 2021), and information retrieval (Djiroun, Guessoum, Boukhalfa, & Benkhelifa, 2024). Today, voice assistant and chatbot platforms such as Google Dialogflow, Facebook Wit.ai, Microsoft Bot Framework, and IBM Watson Assistant enable user interaction via natural language using speech or text (Quamar et al., 2020). From Looker to Power BI, Quicksight to Tableau, major BI products are moving beyond dashboards and reports to bring newer data experiences and conversational analytics to the forefront (Fulara, 2024). Conversational interfaces allow non-technical users, including business owners and managers, to investigate their data, examine different KPIs, and gain business insights by building their dashboard without support from someone with technical expertise (Quamar et al., 2020).

DL, a subfield of ML, has shown great potential in improving BI processes by automatically analyzing complex and large data sets (Gholami et al., 2023). DL enables BI to generate dashboards (Deng, Wu, Qu, & Wu, 2023; Ma et al., 2021), analyze customer feedback (Gholami et al., 2023), cryptocurrency price forecasting (Yasir, Attique, Latif, Chaudhary, Afzal, Ahmed, & Shahzad, 2020), and automated credit scoring (Fombellida, Martin-Rubio, Torres-Alegre, & Andina, 2018).

Developments have significantly influenced trends in BI in genAI. Since OpenAI's public announcement of ChatGPT, the most popular form of genAI, on November 30, 2022, it has captured the attention of all interested parties, including businesses, consumers, regulators, and public policy leaders (Shankar, 2024). While traditional applications of AI in BI have focused heavily on analytical and predictive capabilities, genAI expands the application landscape by facilitating the creation of new data and content that can improve decision-making processes and strategic foresight (Arjunan & Umamageswari, 2024). Advances in AI, such as genAI, have further enhanced the capabilities of NLP, from text understanding to natural language generation (French & Shim, 2024). Insightful data stories and summaries, AI-calculated formulas, and auto-complete SQL queries in dashboards are enabled by LLMs, while genAI enables us to create entirely new experiences (Fulara, 2024). GenAI enables more advanced narrative generation and data analysis, significantly transforming automated insights and reporting in BI (Arjunan & Umamageswari, 2024). According to Andrade (2024), IBM's genAI-powered BI (gen BI) vision includes the following:

- Conversational Experience: Users can interact with a speech assistant by asking natural language questions and getting quick and relevant answers without requiring technical expertise.
- AI-powered Business Consultant: GenAI advisors can make suggestions even when users don't know what to ask.

- Intelligent Metrics and Alerts: GenAI can be used to define KPIs and monitor and alert systems in real time.
- Adaptability for Every User: The GenAI assistant can adapt to users' preferences, thanks to its ability to distinguish subtleties in writing and understand business terminology.
- Trust and Explainability: GenAI can be used to ensure answers are fact-based by providing insights derived only from validated business data and KPIs.
- Automated Data Enrichment: GenAI assistant can be used to simplify analysis and automate business context, reducing the time analysts spend on manual business processes
- Automated Metrics Creation: Data professionals can use GenAI to automate the development of KPIs.

2.1.6 The impact of business intelligence on organizational performance

Bisack III (2017, p.10) described the BI process as "Finding Nuggets in the Noise". The BI system has an integrated structure and enables data-driven insight generation that contributes to companies' strategic decision-making processes. The potential of BI in management and organisational decision-making practices has been well-documented. The rationale behind companies' investments in BI is threefold: to capture new revenue opportunities, to increase operational efficiency, and to optimize the return on information technology (IT) investments in managing customer relationships and enterprise resource planning (Singh & Nayeem, 2011). With BI, companies can effectively analyse data, measure historical performance, and make more robust predictions for the future (Singh & Nayeem, 2011). This enables managers to make more informed decisions, improving the customer experience. Research in the field of ESG indicates that a significant proportion of data stakeholders, 57%, regard BI as critical to their organisation, and that 75% consider BI essential to their success (Leone, 2022). A pharmaceutical company, for instance, generated up to $600 million in additional revenue thanks in part to more effective marketing strategies driven by good BI (Lönnqvist & Pirttimäki, 2006). Integrating BI within IT departments has been shown to enhance operational efficiency, empower senior management, and facilitate enhanced productivity within the IT department (Sakys & Butleris, 2011).

2.2 Generative artificial intelligence (GenAI)

GenAI techniques have been in existence for a considerable period; however, they have only recently begun to gain prominence in academic circles, popular media, and online forums following the release of ChatGPT (Susarla, Gopal, Thatcher, & Sarker, 2023). However, the initial findings in the genAI field were insufficient to facilitate a comprehensive understanding of conversational content and the generation of new texts, thus not being classified as genAI in the present context (Gupta, Ding, Guan, & Ding, 2024).

In November 2022, OpenAI's ChatGPT demonstrated the potential of genAI to increase and make AI accessible to all users with no prior technical background (Sekli, 2024). After the beta version's release, ChatGPT amassed over 100 million users within two months (Susarla et al., 2023). In response, OpenAI's competitors developed GPT-4 and analogous models shortly thereafter (Sætra, 2023). The proliferation of ChatGPT has been accompanied by a growing recognition of its capabilities, including language translation, text generation, text summarization, text classification, question answering, search, and named entity recognition (French &

Shim, 2024). Consequently, the utilisation of Generative Pretrained Transformers (GPTs) has seen a significant surge in popularity.

2.2.1 History of GenAI

This section explains the historical background of genAI based on the relevant literature. To present the historical development more systematically, significant events in genAI history are summarized in Figure 8.

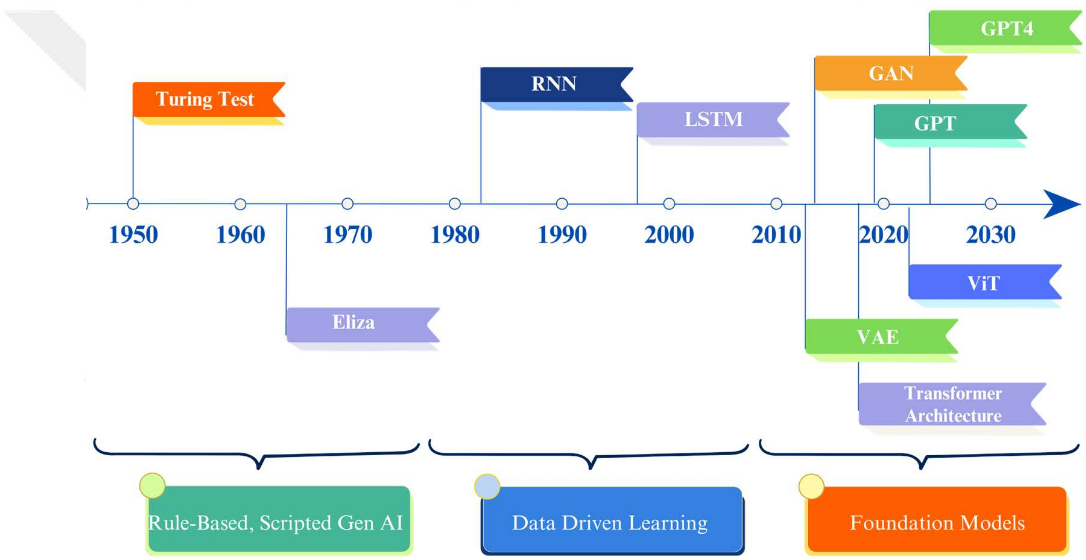

Figure 8. Significant events in the GenAI history
Source: Singh et al. 2024 (Adapted and redrawn by the author)

Early Developments: The origins of DL and genAI have their roots in 1943, before the age of digital computers, when work was done on understanding the brain's workings and creating an artificial model (Strawn, 2024). The first step towards AI was taken with the research article "A Logical Calculus of the Ideas Immanent in Nervous Activity" by Warren McCulloch and Walter Pitts (Pavlik, 2023). McCulloch and Pitts laid the foundation for the subsequent development of artificial neural networks by proposing that neurons could be modeled as binary devices that perform simple logical operations (Strawn, 2024). Piccini's (2024) article states that this work is the first modern computational theory of the mind and brain. Later, in 1950, British mathematician and computer scientist Alan Mathison Turing proposed the Turing test, a mathematical model of computation that describes an abstract machine, in her work "Computing Machines and Intelligence" (Rojas, 2024). Turing's "Machine can think" hypothesis established the foundations of machine intelligence, stating that machines have a mind (Nath, 2020). In 1956, computer scientists John McCarthy and his colleagues Marvin Lee Minsky, Nathaniel Rochester, and Claude Elwood Shannon published a paper titled "A Proposal for a Dartmouth Summer Research Project on Artificial Intelligence", introducing the term AI (Rojas, 2024). In 1957, Frank Rosenblatt created the Perceptron, an electronic device constructed according to the biological principles proposed by McCulloch and Pitts that demonstrated the ability to learn (Strawn, 2024). The Rosenblatt perceptron, as a type of artificial neuron, forms the basis of machine learning (Strawn, 2024). Although the discovery of perceptrons was initially celebrated for their potential in AI, they were later criticized for being limited to linearly separable problems (Strawn, 2024). Towards the end of the 1950s, genAI models were based on probabilistic methods such as hidden Markov and Gaussian mixture models to produce limited outputs (Singh et al., 2024). Markov models (HMMs) have achieved a significant milestone towards content generation by providing a probabilistic way to predict sequences (Huang, Wang, & Zhang, 2024). Early AI research in the 1950s and 1960s generally focused on problem solving and symbolic approaches (Balasubramaniam, Chirci, Kadry, Agoramoorthy, P., K., & A., 2024). In 1964, Joseph Weizenbaum, an MIT computer scientist, developed ELIZA, the first text-based natural language processing application (Stryker & Scapicchio, 2024).

1970-2000: In the 1970s, AI began to be viewed with skepticism, and support began to be reduced or withdrawn as promises previously made were not fulfilled (Guo & Yu, 2021). With the renewed movement in neural network research in the 1980s, the shortcomings of the early perceptron were resolved thanks to contributions from various researchers, including Paul Werbos, Geoffrey Hinton, Yoshua Bengio, and Yann LeCun (Pavlik, 2023). In the 1980s, recurrent neural networks (RNNs) gained popularity as a method of sequentially processing data while preserving previously stored information from earlier inputs through a feedback loop, enhancing their applicability for contextual tasks (Singh et al. 2024). Also, interest in neural network research increased again with the introduction of Hopfield's Hopfield network in 1982 (Guo & Yu, 2021). Developments in this period, such as Hopfield networks, backpropagation mechanisms, and early research on neural network designs, including RNNs, laid the foundations for demonstrating the capacity of machines to produce sequences and patterns (Pathak & Pallasena, 2025). Backpropagation as an optimization technique, has made possible neural networks to be trained more effectively (Huang, Wang, & Zhang, 2024). In 1986, Rumelhart concentrated on RNN training by extending the backpropagation algorithm to data sets (Pathak & Pallasena, 2025). In 1990, Elman advanced RNN research by playing a role in developing and popularizing a simple, recurrent structure RNN for learning temporal dependencies in sequential data (Pathak & Pallasena, 2025). An RNN is a network of multiple neural networks that feed input and output while analyzing text (Tauili, 2023). In a 1997 paper, Sepp Hochreiter and Jürgen Schmidhuber stated that LSTM (long short-term memory) is a different way to feed input and output while analyzing text (Tauili, 2023). These developments have shaped Today's AI architecture (Pathak & Pallasena, 2025).

2000-Current: In the 2000s and 2010s, data availability and computational power enhancements made DL more implementable (Singh et al., 2024). In 2013, VAEs were introduced by Kingma & Welling (Balasubramaniam et al., 2024). They added a probabilistic element to the decoder and encoder components, enabling the generation of diverse and different data samples as a special type of autoencoder (Singh et al., 2024). VAEs provided a different path for conditional generation, widely used in applications such as image-to-image translation (Balasubramaniam et al., 2024). Also, a significant advancement for genAI came in 2014 when Ian Goodfellow introduced (Generative Adversarial Networks) GANs (Balasubramaniam et al., 2024). In an influential 2014 paper on GANs, two neural networks were pitted against each other in a zero-sum game, one generating synthetic data and the other evaluating those examples with real data, to create new images that were very similar to the training data but not identical (Singh et al., 2024). These developments pioneered generative modeling and formed the basis for hundreds of extensions and applications for image generation, data augmentation, audio, multimodal systems, domain adaptation, and many other use cases (Pathak & Pallasena, 2025). In 2017, the Transformer Architecture was introduced by Vaswani (Bouschery, Blazevic, & Piller, 2024). Transformer architecture and diffusion models have increased the performance of text and image generation models and enabled them to be adaptable to a wide variety of task-specific applications (Hagendorff, 2024). In 2019, Radford developed the GPT, which can train and generate text across a broad spectrum of NLP tasks (Pathak & Pallasena, 2025). However, generative models have not been recognized by the broad public until now due to deficiencies such as user-friendly graphical user interfaces, dialogue optimization, and output quality (Hagendorff, 2024). ChatGPT, launched by OpenAI with support and integration from Microsoft in late 2022, has become a significant development that has attracted public interest in the field of genAI (Cobb, 2023). ChatGPT offers the first practical and accessible chatbot online interface for free (Gupta et al., 2023). Even though it has already gained recognition as a serious challenger in many different sectors and applications, genAI is still in the initial stage of development (Rojas & Monroy, 2024).

2.2.2 The types of GenAI models

GenAI models use DL techniques and neural networks to examine and understand content and produce outputs similar to human-generated outputs (Ray, 2023). The milestone model architectures of genAI models that have evolved over the last twelve years or more include Variational autoencoders (VAEs), GANs, diffusion models, and Transformers (Stryker & Scapicchio, 2024). These models use the insights gained by learning the distributions and patterns of training data to generate new content triggered by new input data (Belcic, 2024). Comparisons of these models can be examined in Table 3.

Table 3. Comparison of GenAI Models

Source: Bandi, Adapa, and Kuchi, 2023

GenAI Models	Architecture Components	Training Method
VAEs	Encoder–Decoder	Variational Inference
Gans	Generator–Discriminator	Adversarial
Diffusion Models	Noising (Forward)–Denoising	Iterative Refinement
Transformers	Encoder–Decoder	Supervised

2.2.2.1 Variational Autoencoders (VAEs)

VAEs are introduced by Kingma and Welling (Feuerriegel, Hartmann, Janiesch, & Zschech, 2023). VAEs aim to obtain a latent representation of the data and generate new examples drawing on this representation (Balasubramaniam et al., 2024). As seen in Figure 9, VAEs have an encoder and a decoder based on a complex probability distribution that allows for even greater variety with the output (Taulli, 2023; Håkansson & Phillips-Wren, 2024) and use variational inference for training (Bandi, Adapa, & Kuchi, 2023). VAEs have been used for natural language generation, face recognition, and anomaly detection (Håkansson & Phillips-Wren, 2024). But VAEs may result in fuzzy or less detailed outputs relative to other models and may have limitations in producing highly realistic and diverse samples (Bandi, Adapa, & Kuchi, 2023).

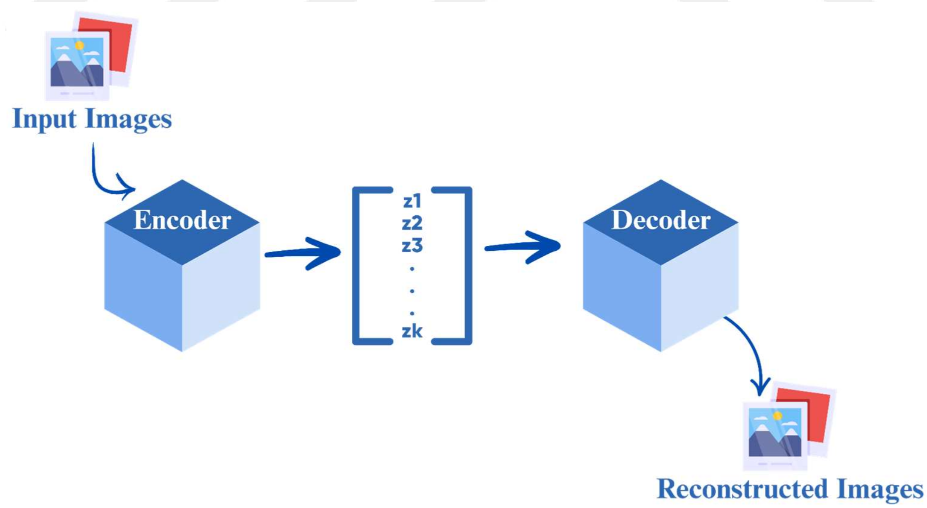

Figure 9. VAE diagram
Source: Balasubramaniam et al., 2024 (Adapted and redrawn by author)

2.2.2.2 Generative Adversarial Networks (GANs)

GANs, introduced by Goodfellow and her colleagues, have gained widespread recognition for their ability to generate realistic data (Balasubramaniam et al., 2024).

GANs, in terms of leveraging modern approaches like DL, are an early form of genAI models (Taulli, 2023). GANs train two neural networks, a generator and a discriminator, to learn models like VAE (Håkansson & Phillips-Wren, 2024), and they are trained adversarially (Bandi, Adapa, & Kuchi, 2023). While the generative algorithm tries to create realistic content, the discriminative algorithm determines whether the created content is real (Mudrinić & Šoda, 2024). This architectural design has had significant and comprehensive effects, enabling the creation of highly realistic visuals and providing a foundation for following advancements in the field of content-generating AI (Balasubramaniam et al., 2024). While GANs have applications for operations such as image generation, GPT models are primarily used for NLP applications such as text generation and language understanding (Ray, 2023). With GANs, high-quality synthetic data can be produced by imitating real data, thus providing benefits while preserving data privacy (Huang, Huang, & Catteddu, 2024).

2.2.2.3 Diffusion Models

The diffusion model has revealed a critical innovation for genAI (Taulli, 2023). Diffusion models create high-quality, realistic images, videos, and animations by adding or removing noise from the output image (Håkansson & Phillips-Wren, 2024). They work through a process known as iterative denoising (Mudrinić & Šoda, 2024) and they use iterative refinement for training methods (Bandi, Adapa, & Kuchi, 2023). This process results in the production of valid and realistic samples that is similar to the original data distribution (Bandi, Adapa, & Kuchi, 2023). Mainstream image synthesis and rendering tools such as Midjourney, Stable Diffusion, and OpenAI's DALL-E 2 are powered by diffusion models (Belcic, 2024).

2.2.2.4 Transformers

The Transformer Architecture, introduced by Vaswani in 2017, forms the basis of most recent language models (Bouschery, Blazevic, & Piller, 2024). For example, it is considered the core of the LLMs, including ChatGPT (Alomari, 2024). Transformers use the attention mechanism to provide weights for the importance of words in a sentence, so the model can concentrate more on what is essential in the text (Håkansson & Phillips-Wren, 2024). In other words, this mechanism considers other words to understand the context and meaning of each word in a sentence (Sekli, 2024).

Additionally, transformers produce consistent sequences through supervised training (Bandi, Adapa, & Kuchi, 2023), and use the encoder-decoder structure in the transformer model (Alomari, 2024) as seen in Figure 10. Encoders are used to take a string of tokens and convert it into a numerical representation (Sekli, 2024). The decoder then takes this representation and produces the relevant translation word by word, ensuring that each new word is consistent with the previous words (Kucharavy et al., 2023). Transformers have revolutionized NLP and effectively capture long-term dependencies thanks to their self-attention mechanism (Bandi, Adapa, & Kuchi, 2023). Approaches such as Generative Pre-Trained Transformer, GPT, and Bidirectional Encoder Representations from Transformers, BERT, use transformer architectures (Håkansson & Phillips-Wren, 2024).

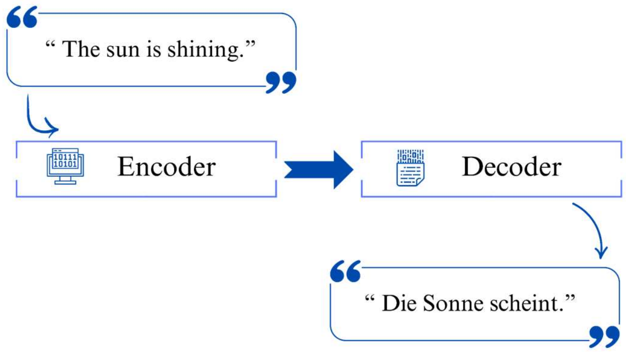

Figure 10. Transformer basic diagram
Source: Balasubramaniam et al., 2024 (Adapted and redrawn by author)

2.2.2.5 Large Language Models (LLMs)

LLM models represent significant progress in genAI by demonstrating impressive capabilities across more diverse tasks than the ideation stage (Sedkaoui & Benaichouba, 2024). Language modeling begins with statistical NLP, which emerged in the 1950s and 1960s (Susarla et al., 2023). Essentially, neural networks, LLMs are trained on large amounts of text data to learn the relationships between words and can then predict the next word that should come in any given sequence of words (Mudrinić & Šoda, 2024). LLM trains large text data to recognize and generate text from large bodies of text using DL and deep neural networks (Håkansson & Phillips-Wren, 2024). In addition to natural language understanding, writing, and text generation capabilities, LLMs creatively address text integrity and predictions, provide sentiment analysis and machine translation, and enable the delivery of chatbots and virtual assistants (Håkansson & Phillips-Wren, 2024). LLMs are a part of a different class of models called foundation models.

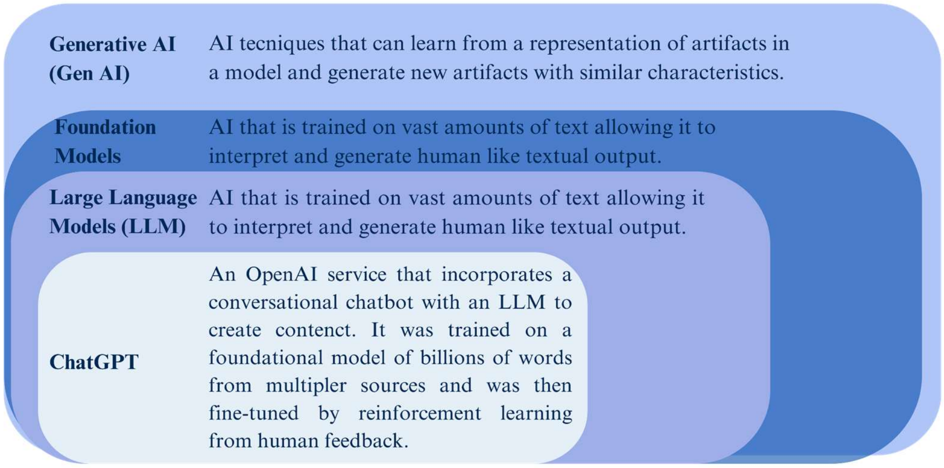

Figure 11. GenAI encompasses various models and types of AI
Source: Osmëni & Ali, 2023 (Adapted and redrawn by author)

As seen in Figure 11, GPT, as in the ChatGPT conversational agent, constitutes a popular family of LLMs used for text generation (Feuerriegel et al., 2023). GPTs were developed by OpenAI between 2018 and 2020 and are a family of autoregressive generative models based on the decoder part of the original Transformer, ranging from 117M (GPT-1) to 175B parameters (Kucharavy, 2023). OpenAI's GPT series, starting from GPT-1 and going all the way to GPT-4, can be considered proof of significant achievements in natural language generation and understanding (Balasubramaniam et al., 2024). The first version of the GPT was launched in 2018 (Ray, 2023). GPT-1 was created to perform NLP tasks such as language modeling and machine translation based on the Transformer, neural network architecture (Gill & Kaur, 2023). GPT-2, on the other hand, made considerable progress beyond GPT-1 by reaching 1.5 billion parameters and became one of the most considerable language models at the time of its release (Ray, 2023). GPT-2 initially performed better than GPT-1, as it produced more precise, more realistic, and more human-like text strings in its generated responses (Gupta, Akiri, Aryal, Parker, & Praharaj, 2023). The GPT-3 model is a 175 billion parameter language model trained on a diverse dataset using naturally generated text from web pages, books, research papers, and social conversations (Dwivedi et al., 2023). Transformer-based language models like GPT-3 are the next level of technology, making them useful for information extraction applications (Bouschery, Blazevic, & Piller, 2024). Despite having fewer parameters, GPT-3.5 performs better on various NLP tasks such as language understanding, text generation, and machine translation (Ray, 2023). By utilizing core models such as GPT-3.5, businesses can automate tasks that require human intervention, resulting in significant operational efficiencies and cost savings (Mudrinić & Šoda, 2024). Using unsupervised pre-training and fine-tuning, ChatGPT can generate human-like responses to natural language queries and topics that resemble human expert responses (Dwivedi et al., 2023). GPT-4 is the model of GPT that has been trained on a large body of text after June 2023 (Gupta et al., 2023). This model takes images and text as a comprehensive, multi-dimensional language framework and produces written output (Gill & Kaur, 2023). A summary and comparison of GPT versions is given in Figure 12 below:

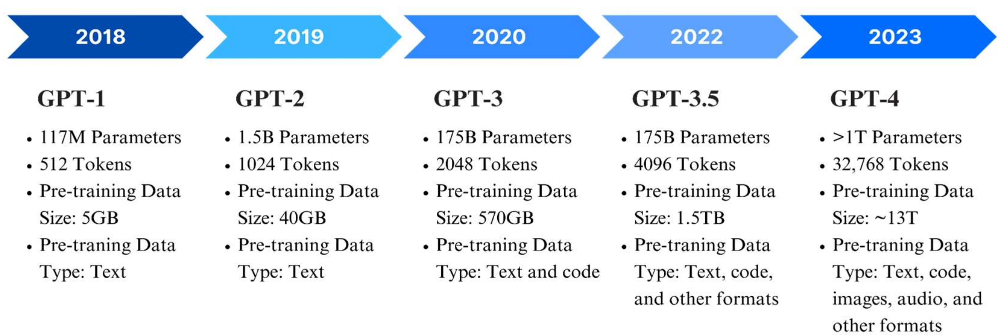

Figure 12. The overview of the GPT family
Source: Alomari, 2024 (Adapted and redrawn by author)

2.2.3 The GenAI use cases

GenAI refers to a class of AI models capable of generating apparently novel content, usually in text, images, or other media (Susarla et al., 2023; Feuerriegel et al., 2023). To create new and diverse content, genAI models use large datasets and complex designs (Gozalo-Brizuela & Merchan, 2024). With the help of generative models, combined with complementary techniques that map the latent high-dimensional semantic space of language or images to multimedia representations of text, audio, or video, it becomes possible to transform inputs such as text into various outputs such as video (Gozalo-Brizuela & Merchan, 2024). GenAI is expected to continue revolutionizing the creative industries and help create art, music, literature, and digital content (Strawn, 2024). A comparison of different use cases can be seen in Figure 13.

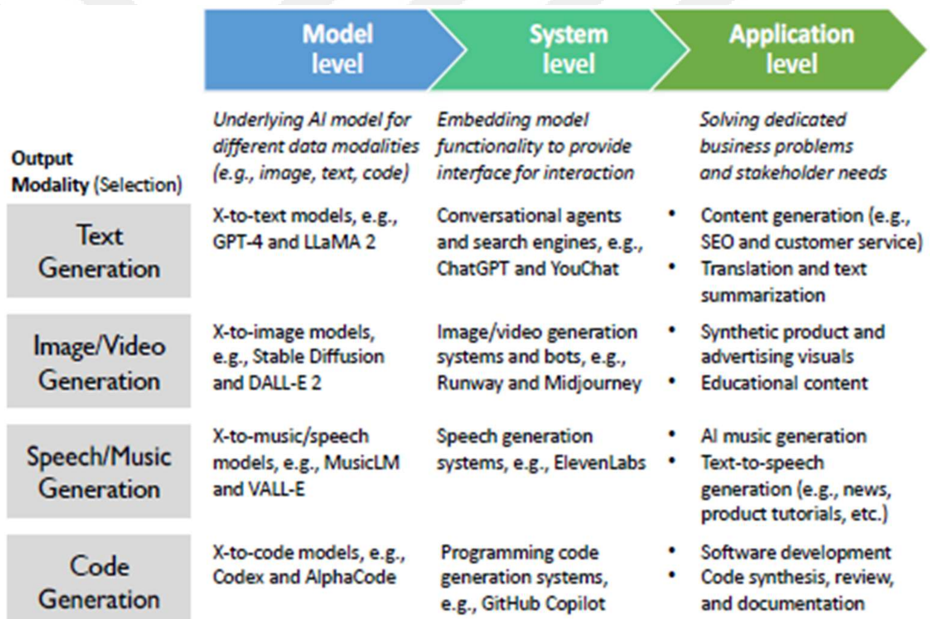

Figure 13. Comparison of different use cases
Source: Feuerriegel et al., 2023 (Adapted)

Text Generation: Text models, mainly centered on conversational chatbots, have revolutionized AI after the release of ChatGPT (Gozalo-Brizuela & Merchan, 2024). Chatbots traditionally use NLP to answer questions asked by users and map them to the best sets of answers available in the system (Dwivedi et al., 2023). NLP's ability to transform text into various textual outputs has undergone a revolutionary transformation thanks to genAI techniques (Bandi, Adapa, & Kuchi, 2023). Even though powerful text generation models were available before ChatGPT was released in November 2022, ChatGPT's ease of use by non-technical users led to its rapid adoption worldwide (Feuerriegel et al., 2023). Text generation is used for translation, text summarization, and content generation (Feuerriegel et al., 2023). In the text-to-text generation process, transformer-based architectures and models that leverage the power of GANs are used (Bandi, Adapa, & Kuchi, 2023).

Visual Generation: The core competency of genAI is based on its adaptive capacity to model data and generate designs based on implicit knowledge derived from real-world data (Ye, Hao, Hou, Wang, Xiao, & Luo, 2024). GAN, diffusion, VAE, and transformers are architectures used to facilitate text-to-image transformation (Bandi, Adapa, & Kuchi, 2023). From the data processing phase to the mapping phase, genAI can play a key role in tasks such as data extraction and augmentation, automatic visualization creation, and answering chart questions (Ye et al., 2024).

As of the launch of DALL-E 2 in 2022, image-generating AI is gradually improving (Gozalo-Brizuela & Merchan, 2024). Artificial images are generated using GANs or propagation models called deep generative models, which have practical applications in design, fashion, marketing, and other creative fields and serve as new forms of visual art (Yehia, 2024). Gen-AI can learn complex patterns, structures, and creative nuances in the visual arts to produce innovative and visually arresting artworks (Pathak & Pallasena, 2025). GenAI's 3D modeling use cases include various applications where 3D designs are fundamental, such as game creation, metaverse, and city planning (Gozalo-Brizuela & Merchan, 2024). Although still a developing field due to the complex nature of video production, examples such as motion capture, digital human videos, and video dubbing are revolutionary uses that could lead to rapid increases in productivity (Gozalo-Brizuela & Merchan, 2024).

Speech/Music Generation: Text-to-speech or audio generation techniques involve converting text into human-like speech and producing music with various vocal styles (Bandi, Adapa, & Kuchi, 2023). Text-to-speech systems produce highly realistic sounds using genAI techniques in speech synthesis (Balasubramaniam et al., 2024). After capturing a three-second audio recording, VALL-E can transcribe the audio and convert written words into speech with realistic intonation and emotion according to the content of the text (Gozalo-Brizuela & Merchan, 2024).

In terms of speech generation, several genAI platforms have been created that enable the creation of text-to-speech speech recordings, such as Coqui, Descript Overdub, ElevenLabs Listnr, Lovo AI, Resemble AI, Replica Studios, Voicemod, and Wellsaid (Gozalo-Brizuela & Merchan, 2024). Voice-activated assistants such as Amazon's Alexa or Apple's Siri are now widely used and can be integrated with smartphones or speakers (Leschanowsky, Rech, Popp, & Bäckström, 2024).

Code Generation: The development of tools that support software engineers to increase the efficiency of their software development processes has historically focused on removing a significant barrier to better, faster, cheaper software development, resulting in higher quality output (Ozkaya, 2023). OpenAI is developing GPTs that increase productivity not only in everyday tasks but also in professional tasks, even without requiring any programming skills (Occhipinti et al., 2025). According to Google's internal sources, ChatGPT has the potential to succeed in interviews for entry-level software engineer positions (Yehia, 2024).

Text-to-code generation enables the entire source code generation concerning the specific business problems, provides suggestions and corrections to eliminate issues in the existing code, and supports the production of documentation for the code, thanks to the code-to-text generation (Bandi, Adapa, & Kuchi, 2023). Code generation will enable the democratization of code, allowing non-technical professionals to easily move between code programs, which could be a significant technological advancement (Gozalo-Brizuela & Merchan, 2024). However, the process must be tested carefully to ensure the code is compatible with the desired outcome (Taulli, 2023). According to McKinsey & Company's research, using genAI-based tools has reduced the time required to document code functionality for maintainability, reduced the time needed to write new code by almost half, and reduced the time necessary to optimize existing code by approximately two-thirds (Deniz, Gnanasambandam, Harrysson, Hussin, & Srivastava, 2023).

2.2.4 The impact of GenAI

GenAI systems analyze large datasets, using complex algorithms and large language models derived from neural networks to learn from datasets and produce new examples similar in format, style, or structure to the original data (French & Shim, 2024). GenAI is more than just rapidly evolving automation; it is an intelligence that can generate knowledge beyond human capabilities, learn from experience, adapt creatively, and think strategically (Occhipinti et al., 2025; Sedkaoui & Benaichouba, 2024).

On the business side, the impact of AI on the organization can be examined along two basic dimensions: whether AI supports or disrupts/threatens the status quo and the level of influence on company and societal outcomes (Shankar, 2024). Innovation and creativity, data-driven insights, consumer-centric product creation, personalized customer experiences, and time and cost savings in marketing initiatives are some of the key benefits of genAI for marketing activities (Shankar, 2024). As these models evolve, companies and individuals will continue to achieve unprecedented gains in content creation, problem solving, and decision making (Gozalo-Brizuela & Merchan, 2024). As companies adopt GenAI, they can drive innovation, enhance efficiency, enable individualized user journeys, and gain a leading position against their competitors (Huang, Ponnapalli, Tantsura, & Shin, 2024). Due to the constant administrative and organizational problems and changes in institutions, genAI is emerging as a new and encouraging solution to increase the performance and efficiency of companies (Naqbi, Bahroun, & Ahmed, 2024). Because of genAI's significant impact on our lives and businesses, working and collaborating with genAI is expected to become more common in the future, even if it is not common now (Nah, Zheng, Cai, Siau, & Chen, 2023).

Enhanced Efficiency and Productivity: The significant efficiency of genAI, which is modifying the current business operations practices, is its most compelling advantage (Rojas & Monroy, 2024). GenAI-powered chatbots, which companies like Amazon and Alibaba use in their customer service processes, can handle millions of customer queries daily with minimal human supervision (Mudrinić & Šoda, 2024). Software developers can increase their productivity by automating repetitive processes, making debugging processes more efficient, streamlining testing, and gaining access to various additional functionality (Yehia, 2024). The use of AI in business processes by white-collar employees will not only enhance customer satisfaction by providing 24/7 customer service but will also reshape processes by relieving employees from repetitive tasks and allowing them to focus on more creative tasks (Corvello, 2024). GenAI can automate and improve decision-making processes by influencing the creation of financial reports and data-driven strategies for marketing and management (Strawn, 2024).

Cost reduction: Kanbach, Heiduk, Blueher, Schreiter, and Lahmann (2023) stated that since genAI reduces the marginal cost of content production, it will support companies' significant business model innovations throughout their processes by enabling them to produce and find value in new ways. GenAI can be applied effectively in real-life contexts and generate large amounts of labor productivity, so it will achieve marginal cost reduction of creative and knowledge-based work (Rojas & Monroy, 2024).

Improved Customer Experience: GenAI has had one of its most visible impacts on customer engagement by changing how companies interact with their customers (Corvello, 2024). GenAI can prepare customized marketing campaigns, advertisements, and product recommendations by investigating user interactions and choices by employing tailored marketing strategies (Huang et al., 2024). Also, chatbots have the potential to transform customer service and support because they have the ability to communicate with users in a human-like and personalized manner (Fegade, Raud, Deshpande, Mittal, Kuul, & Khanna, 2023). Retailers using GenAI are even shaping virtual shopping assistants by offering personalized guidance and recommendations that replicate the in-store online experience (Huang et al., 2024). This increases customer satisfaction, sales, and loyalty rates.

Innovation and New Business Models: GenAI creates a level playing field by providing access to resources, technology, and knowledge for innovators from all locations and socially and economically diverse backgrounds (Kanbach et al., 2023). Yue, Chu, Chung, and Iu (2023) showed that ChatGPT can enable all individuals, independent of their financial knowledge, to make strategic investment decisions and ensure fairness. GenAI supports faster decision-making regarding corporate operations, increases the accuracy of predictions, and makes the development of new products and services easier (Corvello, 2024). While traditional AI systems have certain limits in optimizing existing processes, GenAI can enable people to jointly generate new ideas and discover innovative solutions that would not be possible with traditional technologies (Corvello, 2024). Integrating genAI into products gives these products the potential to increase their price as smarter software products (Corvello, 2024).

2.2.5 Challenges of GenAI

GenAI is considered an impressive technology. However, it is also the subject of intense debates in ethics, data quality, and regulatory governance (Arjunan & Umamageswari, 2024). GenAI tools, especially ChatGPT, negatively impact society and cause users to be concerned about using these tools (French & Shim, 2024). Because genAI outputs produce complex outputs that appear convincing despite containing factual errors, rather than simple decisions, they are more difficult to evaluate (Schneider, Kuss, Abraham, & Meske, 2022). Below, this section discusses the broader social impacts such as job displacement, bias and ethical concerns, quality of training data and inaccurate outputs, copyright violation, environmental concerns, privacy and security, user trust and acceptance. As the use of genAI increases and becomes more popular, these challenges have become increasingly visible. The industry's current state shows the urgent demand to carefully assess opportunities against risks and construct extensive strategies that not only utilize the benefits of genAI but also protect against its potential problems (Huang et al., 2024).

Job displacement: The emergence of genAI, especially large language models such as GPT-3 published by OpenAI in November 2022, has led to the emergence of a new era of labor productivity, innovation, and economic growth (Occhipinti et al., 2025). From ChatGPT to GPT4, DALL-E 2/3 to Midjourney, the latest wave of AI has generated unprecedented global interest, with both enthusiasm for broad potential applications and deep concern about the risks of intelligence surpassing even humans (West et al., 2023). According to Gartner, more than 100 million workers will use robo-colleagues to support their jobs by 2026 (n.d.). Estimates, considering other productive models and complementary technologies, suggest that 49% of workers may have half or more of their tasks subjected to LLMs (Eloundou, Manning, Mishkin, & Rock, 2023). Thus, many time-consuming, repetitive processes will be automated. The development of genAI technology has given rise to two different views on the workforce. According to the first view, many existing jobs may be replaced or eliminated due to the automation of repetitive tasks by genAI (Sedkaoui & Benaichouba, 2024).

On the other hand, many economists argue that genAI shares similar characteristics with previous technological developments, such as the Internet or computers, and that this trend is simply a continuation of the historical pattern of technology-driven progress (Occhipinti et al., 2025). Despite the recent interest in ChatGPT, research on AI is still in its infancy, and data is limited, so claims about job losses are anecdotal or future projections (Dahlin, 2024). Therefore, the net impact of genAI on employment is debatable and requires additional scrutiny (Sedkaoui & Benaichouba, 2024).

Bias and Ethical Concerns: GenAI raises questions of fairness, bias, and accountability that arise from the ability to autonomously generate content, leading to ethical dilemmas (Mudrinić & Šoda, 2024). Algorithmic bias occurs when AI models unintentionally reinforce or magnify biases already present in the data they are trained on (Shankar, 2024). If a human operator does not check and verify the outputs of ChatGPT, it can produce factual inaccuracies, logical errors, bias, and plagiarism (Silva et al., 2024). GenAI models may unknowingly receive biases existing in the training data or the design of the algorithms, leading to disproportionate representation and unequal treatment of users in specific demographic categories (Huang et al., 2024). Using this biased data can have serious consequences. For example, AI-powered marketing campaigns can unintentionally use biased data to discriminate against specific customer segments, damage brand reputation, and alienate essential customers from the brand (Shankar, 2024). Ethical concerns are vital to eliminate biases, ensure human control, and establish frameworks for responsible AI development from initial concept to implementation and application (Sedkaoui & Benaichouba, 2024).

Quality of Training Data and Incorrect Outputs: While GenAI brings some risks common to many information systems, such as the accuracy of the data used, it also brings risks specific to this technology, such as hallucination or providing completely false information (Zarifis & Cheng, 2024). Synthetic creation of media such as deepfakes, a capability of GPT, can pose risks such as privacy violations and misinformation, and challenge traditional notions of consent and authenticity (Arjunan & Umamageswari, 2024). Although OpenAI has implemented a content policy for ChatGPT, harmful or inappropriate content may still be produced due to algorithmic restrictions or unauthorized changes (Shankar 2024; Yehia, 2024). To prevent this situation, it is essential to avoid harmful or offensive information in the training data and remove such information if any (Nah et al., 2023). However, this process is costly due to the large amount of data. (Nah et al., 2023).

At the same time, since the internal logic and mechanism of the data-driven DL model is still a black box for humans, assumptions about why the current output was generated can neither be testable nor disprovable (Wu et al., 2023). For example, in the tightly controlled healthcare sector, over-reliance on AI-generated content can lead to disastrous outcomes such as poor patient treatment (Nah et al., 2023).

Copyright Violation: Copyright is a legal concept that ensures the originality of creative works by documenting them in an immaterial form (Yehia, 2024). Intellectual property and copyright issues for genAI become relevant, particularly regarding the ownership and use of data used for model training and the outputs produced (Balasubramaniam et al., 2024), as some of the content created by genAI may be the original work of other creators, which is protected by copyright laws and regulations (Nah et al., 2023). In addition, the information provided as input is a concern for companies. For example, the ability of individual employees to access tools such as ChatGPT independently of corporate applications could lead to bottom-up distribution dynamics that challenge centralized AI governance methods (Schneider et al., 2022). Due to the impressive capabilities of GenAI, employees may be strongly motivated to use these tools and increase their productivity, but it is emphasized that adequate governance is needed if it does not align well with corporate policies (Schneider et al., 2022).

Environmental Concerns: ChatGPT consumes a large amount of hardware resources during training because it contains a large number of parameters and pre-training data (Wu et al., 2023). Because the model training and deployment process for genAI causes a significant carbon footprint (Jovanović & Campbell, 2022).

According to Yehia (2024), the annual electricity consumption of 175,000 Danish families was similar to the electricity consumption of OpenAI in January 2023, and AI could affect the electricity use of millions of people. However, even if this is seen as a problem now, according to Gartner, 30% of GenAI applications will be optimized by sustainability initiatives using energy-efficient computing methods by 2028 (Chandrasekaran, 2024).

Privacy and Security: ChatGPT was developed for educational purposes using a significant amount of sensitive and personal data that poses a potential threat to privacy (Yehia, 2024). This is an issue that has attracted attention from both individuals and institutions. From an institutional perspective, industrial data often exists as isolated islands due to privacy concerns, industry competition, administrative processes, and related challenges (Gupta et al., 2024). The use of ChatGPT by users as a regular part of daily operations and the regular entry of sensitive or confidential information into the system can compromise data security and create breaches (Nah et al., 2023). GenAI also poses significant security risks and jeopardizes data privacy, cybersecurity, and the integrity of digital systems (Mudrinić & Šoda, 2024). While laws such as the California Consumer Privacy Act and the General Data Protection Regulation impose strict rules on data usage, the scope of AI's data usage makes it more vulnerable to potential breaches that could lead to significant fines and reputational damage (Shankar, 2024). Despite the transformative impact of genAI, it comes with ethical complexities surrounding the production of deepfakes, which are persuasive synthetic media, and deepfakes bring inherent risks, including the spread of misinformation and potential breaches of privacy and security (Balasubramaniam et al., 2024).

User Trust and Acceptance: In situations involving uncertainty and vulnerability, trust is the attitude that an agent will help individuals achieve their goals (Lee & See, 2004). In AI technologies that rely heavily on ML algorithms, algorithms are described as black boxes because their working mechanisms are challenging to explain, and human actors cannot understand the ways in which artificial agents learn and arrive at a specific answer (Choung, David, & Ross, 2022). For this reason, despite widespread positive perceptions of the potential of AI, barriers such as lack of trust and knowledge remain (Acosta-Enriquez et al., 2024).

Integrating genAI in a way that users can trust is essential for the adoption of this technology in many areas, from healthcare to education, from finance to law. According to Frank, Chrysochou, Mitkidis, and Otterbring (2024), specific consumer-oriented industries, such as services and retail, may have a distinct advantage in successfully implementing AI technology over more sensitive areas such as medical and law. In an era of AI-driven change, human reluctance to adopt this powerful technology has emerged as one of the most critical barriers (Frank et al., 2024). Actions required for genAI include changing how this technology works and how its trustworthiness and value are communicated (Zarifis & Cheng, 2024). Recently, government organizations, such as the OECD and the EU, technology companies such as Google and Microsoft, and professional organizations such as IEEE have published frameworks for the development and deployment of trustworthy AI (Choung, David, & Ross, 2022). At the user's point, it is recommended that they do not unquestioningly trust the answers provided by genAI and run verification processes before accepting the answers (Nah et al., 2023). GenAI can produce compelling artifacts when implemented widely, but trust in those artifacts and control over their creation are necessary for user adoption (Jovanović & Campbell, 2022).

2.3 Technology acceptance and adoption literature

In the AI adoption literature, both traditional adoption and acceptance models and extended or hybrid models that consider AI features have been used. Models such as the Theory of Planned Behavior (TPB) (Chai, Lin, Jong, Dai, Chiui, & Qin, 2021), Technology Acceptance Model (TAM) (Choung, David, & Ross, 2022; Ishengoma, 2024; Leschanowsky et al., 2024; Mogaji, Viglia, Srivastava, & Dwivedi, 2023; Seo & Lee, 2021; Shaengchart, 2023), Diffusion of Innovation Theory (DOI) (Ghimire & Edwards, 2024; Gupta, Nair, Mishra, Ibrahim, and Bhardwaj, 2024; Patnaik & Bakkar, 2024), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Rana, Siddiqee, Sakib, & Ahamed, 2024) and UTAUT2 (Acosta-Enriquez et al., 2024; Ho & Cheung, 2024; Nawaz, Sanjeetha, Murshidi, Riyath, Yamin, & Mohamed, 2023) have been used to explain users' AI technology acceptance and adoption behavior.

However, traditional models have been criticized due to the development of AI technology and the differentiation of the context of this technology from other technologies. For example, it is stated that traditional technology adoption models are more suitable for using non-intelligent technologies, ignoring the characteristics of AI technology (Yang, Luo, & Lan, 2022). Also, Lu, Cai, and Gursoy (2018) stated that ease of use is an essential factor in the context of AI and service robots because users do not undergo any learning process when interacting with service robots. In response to these criticisms, AIDUA was developed by Gursoy, Chi, Lu, and Nunkoo (2019). Later, AIDUA is also criticised by Yang, Luo, and Lan (2022).

Factors such as social influence, hedonic motivation, and anthropomorphism are more suitable for Social-oriented AI devices than Task-oriented AI devices (Gupta, 2024). They proposed the T-AIA model.

In order to understand the factors affecting the adoption of genAI in BI applications, this study examines both traditional adoption and acceptance theories. Also, new AIDUA and T-AIA theories are examined.

2.3.1 Theory of Reasoned Action (TRA) / Planned Behavior (TPB)

TRA was introduced by psychologists Fishbein and Ajzen in 1975 (Armitage & Conner, 2001). According to TRA, individuals' intentions are shaped by attitudes toward the behavior in question (the individual's evaluation or appreciation of the behavior in question) and perceptions of subjective norms (the social pressure or expectation to engage or not engage in the target behavior) factors (Kuo, Roldan-Bau, & Lowinger, 2015). The main assumption of TRA is that intentions are shaped by attitudes and subjective norms, and behaviors are determined by intentions.

Later, TPB was introduced by Ajzen in 1985 (Salama & Farag, 2004). TPB extends TRA by adding perceived behavioral control as a third component. The perceived behavioral control (PBC) construct added to the TPB explains a significant amount of variance in intention and behavior, independent of the TRA variables (Armitage & Conner, 2001). TRA and TPB both argue that individuals' beliefs about norms and behaviors influence their subjective norms and behavioral attitudes (Börstler, Ali, Petersen, & Engström, 2024).

The study by Chai et al. (2021) conducted a study based on TPB and examined five factors to measure behavioral intention to learn AI. The study found that self-efficacy in learning AI, AI readiness, perceptions of using AI for social good, and AI literacy directly or indirectly influenced behavioral intention.

2.3.2 Technology Acceptance Model (TAM)

TAM was developed by Fred Davis in 1989, and it suggested that the ease of use and usefulness of a technology significantly influence users' intention to use it (Shaengchart, 2023). The power of TAM is based on its ability to make sense of the complicated phenomenon of technology adoption by simplifying it into two key constructs and establishing a structured approach for user behavior (Ishengoma, 2024). According to the TAM perspective, attitude plays a mediating role between perceptions and behavioral intention (Ho & Cheung, 2024). Later, the TAM model was extended as TAM2 and integrated variables such as subjective norm, image, job relevance, and output quality (Ishengoma, 2024). Later, additional constructs such as perceived enjoyment and computer anxiety were added to the TAM3 model to understand the adoption of new technologies (Gupta et al., 2024). The elements of the TAM, TRA, and TPB are given in Figure 14 below:

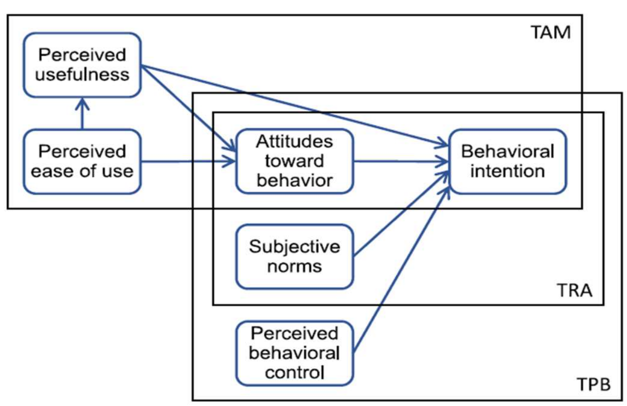

Figure 14. Key constructs of TAM, TRA, and TPB
Source: Börstler et al., 2024 (Adapted)

TAM theory has been used in different studies to understand the adoption and widespread use of AI applications. According to Kelly, Kaye, and Oviedo-

Trespalacios (2023), the most widely used theory to evaluate user acceptance of AI technologies is the Extended Technology Acceptance Model (TAM). For example, Shaengchart (2023) found that higher education students' ChatGPT adoption intentions using TAM revealed that perceived usefulness and perceived ease of use components significantly influenced students' ChatGPT technology adoption intentions. Leschanowsky et al. (2024), in their literature review study on privacy, security, and trust perceptions in conversational AI, stated that researchers expanded the TAM by adding factors such as perceived privacy risk, perceived security risk, or safety risk. Seo and Lee (2021) integrate the original constructs of Technology Acceptance Model (TAM) with trust, perceived risk, and satisfaction in a robot service restaurant environment, showing that trust significantly increases perceived usefulness and perceived ease of use towards a service robot, and perceived risk decreases and satisfaction increases with increasing trust in the robot service. Choung, David, and Ross (2022) contributed to the development and application of TAM in AI-related applications through their research and presented a composite trust measure that can be used in further studies for trustworthy AI. They suggested that by validating the important role of trust and demonstrating its additional benefits over TAM, trust and the TAM framework could be applied to AI-enabled applications, particularly technologies with higher risks and anthropomorphic features (Choung, David, & Ross, 2022). Ishengoma (2024) stated in her literature review that researchers should also evaluate the capability of emerging technologies, such as the use of AI, to better identify technological factors that can encourage technology adoption in library environments and increase the predictive power of TAM. According to Mogaji et al. (2023), although extended TAM models are widely used in the literature as a choice to evaluate users' acceptance of AI technologies, the dynamic change of AI devices has undermined the predictability of the traditional TAM model.

2.3.3 Diffusion of Innovation Theory (DOI)

Communication studies professor Everett Rogers introduced the DOI theory in 1962 in his groundbreaking book The Diffusion of Innovations (Yu, 2022). The success of any innovation depends on good communication channels, the characteristics of the innovation, the characteristics of the adopters, and the social system (Yu, 2022).

DOI has been used to understand AI acceptance in different studies. This theory emphasizes the importance of how to use social networks in the context of ChatGPT, explaining the advantages of the technology to potential users and encouraging adoption (Gupta et al., 2024). Patnaik and Bakkar (2024) used an integrated framework of the DOI theory with transformational leadership to investigate transformational leadership and AI adoption. Ghimire and Edwards (2024) analyzed the key factors affecting educators' perceptions and acceptance of GenAI and LLMs through the TAM and DOI frameworks. According to the study, there is a strong positive correlation between the perceived usefulness and acceptance of GenAI tools, with perceived ease of use being a significant component affecting acceptance (Ghimire & Edwards, 2024).

2.3.4 Unified Theory of Acceptance & Use of Technology (UTAUT)

UTAUT was developed by Venkatesh in 2003, and it intends to clarify technology adoption by combining eight models, including TAM and TPB (Salama & Farag, 2024). Performance expectancy refers to the extent to which technology use improves job performance, while effort expectancy refers to the level of ease involved in the process of technology use (Gupta et al., 2024). Facilitating conditions refer to the impact of institutional and infrastructural and technological infrastructure on technology use, and social influence refers to the impact of other user beliefs on technology adoption (Gupta et al., 2024). The elements of the UTAUT model are given in Figure 15 below:

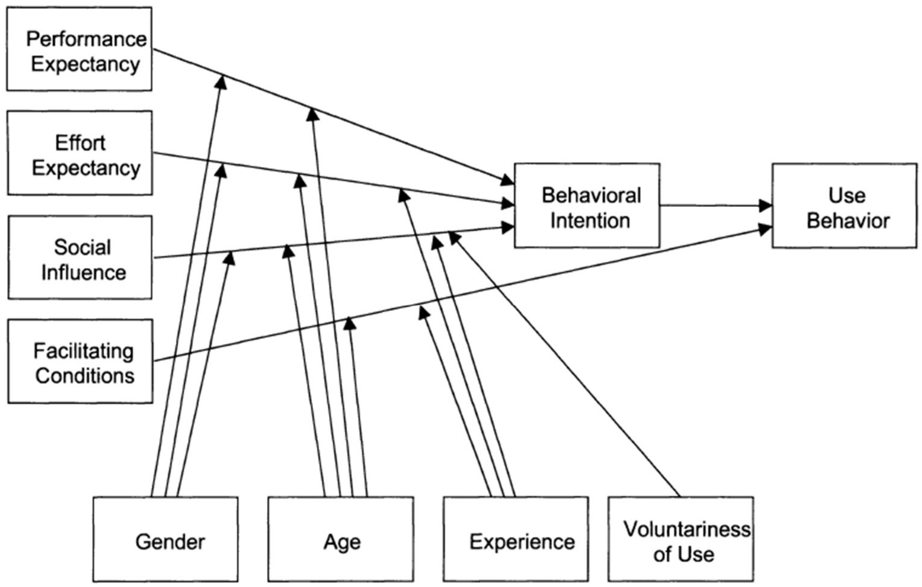

Figure 15. The Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh, Morris, Davis, & Davis (2003) (Adapted)

Regarding AI adoption, the UTAUT and UTAUT2 models have been used in the literature by adding different constructs. Rana et al. (2024) adopted the UTAUT model and added additional trust and privacy constructs. Ho and Cheung (2024) extended the UTAUT2 model with the trust and attitude structures towards AI and the interest of the news media to measure the public perception towards the emerging AI technology of autonomous passenger aircraft, taking the UTAUT2 model as a reference in their study. Acosta-Enriquez et al.'s (2024) literature review strengthens the importance of UTAUT2's primary constructs, such as performance expectancy, hedonic motivation, perceived ease of use, and social influence in predicting AI adoption intentions and behaviors between students, faculty, and administrative staff.

Nawaz et al. (2023) used the unified theory of technology acceptance and use 2 (UTAUT2) to investigate ChatGPT acceptance and included personal innovativeness as both a dependent and moderating variable.

2.3.5 Artificially Intelligent Device Use Acceptance (AIDUA)

Traditional technology adoption models, such as the TAM and UTAUT models, are unsuitable for investigating intelligent technology adoption (Gupta, 2024). Intelligent technologies include advanced cognitive abilities such as AI, genAI, and ML. Apart from the AIDUA model, traditional technology acceptance models have been developed to use non-smart technologies, ignoring the features of AI technology (Yang, Luo, & Lan, 2022).

In the AIDUA model, Gursoy et al. (2019) propose that customers examine a multi-stage decision-making process using the Cognitive Evaluation Theory to determine their willingness to accept the use of AI devices throughout service interactions with the AIDUA model they propose. This multi-stage evaluation process is divided into three stages: primary evaluation, secondary evaluation, and conclusion. According to Lazarus' framework, individuals go through three stages in the decision-making process: assessing importance (primary appraisal), analyzing behavioral options (secondary appraisal), and generating emotions in response to stimuli that lead to behavioral intentions (Gursoy et al., 2019). With primary evaluation, individuals first evaluate the extent to which the stimulus factors are relevant and how they threaten or benefit the individual's values or beliefs related to achieving goals (Gursoy et al., 2019). In the secondary evaluation stage, individuals primarily evaluate the decision options and consequences of each decision with respect to emotions and then form their emotions in the direction of using AI devices in service delivery (Gursoy et al., 2019). When the user believes that the use of AI devices is essential based on social influence, hedonic motivation, and anthropomorphism factors in the primary evaluation stage, she carefully weighs the costs and benefits by taking into account performance expectancy and effort expectancy in the second evaluation stage (Gupta, 2024). In the outcome stage, after complex evaluation processes, individuals will determine their willingness to accept the use of AI devices or their objection to the use of AI devices during service encounters, which will ensure the formation of emotions toward the use of AI devices (Gursoy et al., 2019). This model aims to investigate customer acceptance (or objection) of AI devices in customer service sectors and whether AI devices will replace humans providing customer service (Gupta, 2024). This study has pioneered new studies in the literature by criticizing existing models in terms of AI adoption.

2.3.6 Task-oriented AI Acceptance (T-AIA)

Yang, Luo, and Lan (2022) proposed a new theoretical T-AIA model for task-oriented AI devices. The three-stage adoption process used in the AIDUA model is also used in this model. However, they want to discriminate between acceptance studies based on task-oriented and social-oriented approaches according to their functions. Yang, Luo, and Lan (2022) stated that task-oriented AI devices use more formal and purely task-oriented dialogues, enabling individuals to achieve functional goals. Therefore, the T-AIA model was proposed based on the assumption that the social influence, hedonic motivation, and anthropomorphism factors used in the AIDUA model are more appropriate for Social-oriented AI devices instead of Task-oriented AI devices (Gupta, 2024).

Using the multi-stage appraisal framework and the Structural Equation Modeling analysis, Yang, Luo, and Lan's (2022) findings present that in the primary appraisal, utilitarian motivation, interaction convenience, and task-technology fit are the factors appraised that are positively associated with perceived competence. Then, in the secondary appraisal, perceived competence is positively associated with flow experience. Finally, flow experiences are positively associated with customers' switching intention in the outcome stage.

2.4 Summary

This chapter has discussed the literature on BI, genAI technology, and technology acceptance models. This study on BI explored the components that are important for BI technology in detail. Then, it examined the development of genAI technology. Finally, after examining the existing acceptance models, we determined the model and methodology we would use. The following sections of the study discuss the research hypotheses and the model proposed for this study.

CHAPTER 3

FRAMEWORK AND HYPOTHESES

GenAI is a type of AI that can generate new and original content by learning from extensive datasets on which it is trained. While traditional AI models are used for predictive tasks such as classification and regression, GenAI generates new data and content. GenAI also profoundly impacts BI by enabling synthesized data, personalized customer experiences, and easier operational capabilities (Arjunan & Umamageswari, 2024). The repercussions of this impact can also be observed in the business sector. For example, major BI vendors, including Microsoft's Power BI, Amazon's QuickSight, and MicroStrategy's BI tools, have begun integrating GenAI capabilities into their products. However, even as GenAI is gaining popularity, Gartner estimates that towards the end of 2025, at least 30% of genAI projects will not be achieved after proof of concept because of the poor data quality, unsatisfactory risk controls, increased costs, or uncertain strategic value (Keen, 2024). Moreover, traditional technology adoption models are more suitable for using non-intelligent technologies, ignoring the characteristics of AI technology (Yang, Luo, & Lan, 2022). Therefore, developments in GenAI pave the way for improvements in technology adoption models. While innovations in GenAI continue to advance, researchers are still developing theoretical frameworks that can comprehensively demonstrate these technologies' complicated dynamics and business implications (Gupta, 2024). In this context, based on the literature reviewed in the previous section, we constructed our theoretical framework using the AIDUA (Gursoy et al., 2019; Vitezić & Perić, 2021; Li, Lin, Chen, & Chen, 2025; Gupta,

2024) and T-AIA (Yang, Luo, & Lan, 2022) models, which can better integrate the features of genAI technology into the adoption model.

The following section formulates our hypotheses using relevant theoretical models. Next, we will explain the research model's structure and conceptual framework. Finally, we will outline this study's contribution to the literature.

3.1 Stage 1: Primary appraisal

During the primary evaluation phase, users first assess the extent to which the stimulus factors are relevant and how these stimuli threaten or benefit the individual's values or beliefs concerning achieving their goals (Gursoy et al., 2019).

In our framework, in addition to the utilitarian motivation and task-technology fit constructs in the T-AIA framework, I added continuous improvement, conversational intelligence, and performance risk as new features of genAI. Including these variables will provide a richer prediction of users' cognitive appraisal. In the original T-AIA framework, the ease of interaction construct was removed from this study. Ease of interaction in the T-AIA framework involves enabling users to utilize task-oriented AI without time and space limitations, and facilitating the receipt of services from these technologies (Yang, Luo, & Lan, 2022). To our knowledge, the most effective way to access BI applications, regardless of time and location, is to use mobile BI applications. However, as mobile BI is scrutinized under companies' cybersecurity policies, users cannot easily access BI tools from anywhere. A study by Verkooij and Spruit (2013) revealed that, according to expert interviews, the most critical risk in mobile BI projects is information security. Experts agree that minimizing the amount of information accessible on mobile devices reduces most information security risks. Therefore, we did not consider this construct in the study.

3.1.1 Utilitarian motivation (UM)

Different consumption motivations are often categorized as hedonic and utilitarian (Qi, Ono, Mao, Watanabe, & Huang, 2025). In these two consumer motivation concepts, utilitarian motivation is associated with the utility and functional value of an object, while hedonic motivation is associated with the emotional or sensory sides of the experience itself (Redda, 2024). Consumers are highly rational and task-oriented in their approach to utilitarian values (Alam, Masukujjaman, & Ahmad, 2022).

Consumer motivations are also determinants of interaction with AI technology. As Yang, Luo, and Lan (2022) mentioned, AI devices are task-oriented and social-oriented according to their functions. In addition, Yang, Luo, and Lan (2022) stated that utilitarian motivation is a more appropriate predictor for the acceptance context of task-oriented AI devices, as stated in the T-AIA model. Customers using task-oriented AI devices are more goal-oriented than those using social-oriented AI devices, who pursue emotional interaction (Yang, Luo, & Lan, 2022). In our research, utilitarian motivation refers to the user's perception that task-oriented genAI is an effective, helpful, functional, and practical tool for evaluating services in BI applications used to perform their tasks. Individuals with utilitarian motivation for genAI can more easily assess this service's contribution, as they focus more on the tangible benefits of BI applications. Previous studies have confirmed that utilitarian value positively affects perceived usefulness (Alam, Masukujjaman, & Ahmad, 2022; Kwon, 2015; Jo, 2023). Hence, the hypothesis is as follows:

H1: Utilitarian motivation has a positive impact on perceived usefulness.

3.1.2 Task-technology fit (TTF)

Goodhue and Thompson (1995) describe task-technology fit as the capacity of a technology to assist users in performing tasks. According to the TTF model, the use of new technologies affects the functions of the technology, and these functions must comply with the needs of users so that they can use the technology confidently (Shahzad, Zhang, Zafar, Ashfaq, & Rehman, 2023). Rational and experienced users will choose the tools and methods that bring the most significant net benefit to their task completion process (Dishaw & Strong, 1999). In other words, users are interested in accessing and using technological tools and in how effectively and efficiently these tools can perform their intended tasks. Dishaw and Strong (1998) stated that there was no direct relationship between TTF and perceived usefulness in their study.

Previous studies found that TTF positively affects perceived usefulness (Al-Emran, 2021; Chakraborty, Troise, & Bresciani, 2025; Rai & Selnes, 2019). In our research, TTF was used to determine the compatibility, adequacy, usefulness, and facilitation levels of genAI-powered BI applications in tasks specified by users. The hypothesis regarding TTF is as follows:

H2: Task-technology fit has a positive impact on perceived usefulness.

3.1.3 Continuous improvement (CIM)

Hall (2004) assumed that a software-based universal intelligence could produce more software, which, in some cases, could enhance its capabilities. GenAI technology, a software-based intelligence, has significantly improved software generation and continues to evolve, producing increasingly better outputs. ChatGPT is based on an ML model that can be continuously trained and enhanced with new data (Gupta, Mufti, Sohail, & Madsen, 2023). To achieve higher-quality outputs from genAI, it is essential to integrate knowledge and critical feedback from experts on AI-type virtual assistants, thereby leading to a continuous skill-building cycle between AI and humans (Sherson & Vinchon, 2024). For example, Madaan et al. (2023) introduced the concept of self-improvement. This approach aims to enhance initial outputs from LLMs through iterative feedback and refinement, inspired by how humans refine their written texts. Welleck et al. (2022) introduced self-correction, an approach that separates a faulty base generator, such as a ready-made language model or a supervised string model, and a separate corrector that learns to correct the defective offspring iteratively. They found that self-correction offers a promising mechanism for utilizing natural language feedback to enhance production. For instance, GPT-4, one of the genAI models, can solve a problem by receiving a response from the environment, such as from the user or the command line, or it can identify and utilize external tools to enhance its performance (Bubeck et al., 2023). All these distinguish genAI technology from traditional systems. In traditional systems, technological contribution is primarily based on the fixed functionality provided by the system. In contrast, in GenAI systems, contribution is based on learning performance and adaptation capacity that improve over time.

Yang and Lee's (2024) study shows that continuous improvement of genAI's recommendations positively affects consumers' perception of its originality. In this research, continuous improvement is closely tied to genAI's ability to enhance its performance by learning from past experiences, refining its capabilities, correcting errors, and becoming increasingly functional. Our study evaluates the impact of

GenAI's ability to improve itself by learning from past experiences and become more advanced, error-free, and competent over time on perceived usefulness. The hypothesis is as follows:

H3: Continuous improvement has a positive impact on perceived usefulness.

3.1.4 Conversational intelligence (CI)

With advances in AI and genAI technologies, emotion analysis and adaptive learning models will further enhance chatbot capabilities, enabling more contextual and human-like interactions (Phadnis, Gadge, & Shah, 2025). Chatbots powered by genAI can reduce costs, provide instant and accurate answers, and enhance users' experiences by offering personalized service (Phadnis, Gadge, & Shah, 2025). According to Brandtzæg and Følstad (2017), for chatbots to be successful, they must assist users in completing a task or achieving a measurable goal effectively and efficiently while being easy, fast, and valuable. Conversational AI enables multiple tasks to be processed simultaneously, allowing systems to operate continuously across various industries, including retail, healthcare, finance, and hospitality. This creates interactions that enhance a more personalized customer experience (Phadnis, Gadge, & Shah, 2025).

On the other hand, a conversational user interface that is not adequately prepared will frustrate users and harm the business (Brandtzaeg & Følstad, 2017). It is stated that users' evaluations of the performance and usefulness of an AI assistant, particularly in terms of its effectiveness, will be influenced by their cognitive perceptions of the intelligence of AI assistants (Ling, Tussyadiah, Liu, & Stienmetz, 2023). However, the study on interaction with conversational intelligence by Ling et al. (2023) mainly focused on customers' intentions towards such systems. However, they have not included perceived usefulness as a possible determinant. This study represents a first step toward providing new insights into dimensions that have not been previously addressed in studies on AI acceptance. The hypothesis is as follows:

H4: Conversational intelligence has a positive impact on perceived usefulness.

3.1.5 Performance risk (PR)

According to the research model presented by Featherman and Pavlou (2023), perceived risk encompasses performance, financial, time, psychological, social, privacy, and general risk. They model performance risk as a precursor to the remaining risk concerns. Perceived performance risk is when the product output fails to provide the desired benefit and does not function as expected (Grewal, Gotlieb, & Marmorstein, 1995). In Section 2.2.4, we have detailed the risks associated with using genAI. Among these, risks such as bias and ethical issues, quality of training data and incorrect outputs, copyright infringement, privacy, and security are included in performance risks.

This study aimed to evaluate the effects of performance risk, failure to meet expectations for genAI-based BI systems, lack of technical maturity, reliability concerns, or error risk on perceived usefulness. Numerous studies suggest that the perception of performance risk has a negative impact on PU (Lee, Oh, & Moon, 2022; Wu & Ho, 2025; Kaushik & Kumar, 2017). For example, Kaushik and Kumar (2017) stated that self-service technologies are perceived as unhelpful and/or difficult to use by users with high performance risk. The hypothesis is as follows:

H5: Performance risk has a negative impact on perceived usefulness.

3.2 Stage 2: Secondary appraisal

In the primary appraisal, individuals evaluate how the stimulus factors threaten or benefit their values or beliefs. Then, in the secondary appraisal stage, individuals primarily evaluate the decision options and their consequences and form their emotions regarding using AI devices in service delivery (Gursoy et al., 2019). Our study identified five predictors from previous studies that significantly affect customers' AI acceptance behavior for the primary appraisal phase.

In this study, the secondary appraisal phase focuses on users' assessment of the perceived usefulness of genAI-powered BI usage, which results in emotions toward genAI-powered BI usage at the end of the secondary appraisal. Perceived usefulness is the degree to which a person believes that he or she can improve his or her job performance when using a particular system (Davis, 1989). Gupta (2024) defined perceived usefulness in his model as the degree to which an entrepreneur believes that using genAI technology in business processes will increase efficiency, productivity, and overall effectiveness, support operational objectives, and address complex tasks in a way that improves upon or complements alternative methods or tools. In our study, perceived usefulness refers to a user's attitude toward the impact of using genAI-powered BI technologies on improving overall performance by streamlining processes in an efficient, effective, and productive manner.

3.2.1 Perceived usefulness (PU) and flow experience (FE), trait curiosity (TC), trust (TAI)

Flow theory was developed by Mihaly Csikszentmihalyi in the 1970s (Pereira, Fernandes, Bittencourt, & Félix, 2022). From a psychological perspective, an individual in a state of flow achieves high levels of concentration, relaxation, anxiety control, and satisfaction while performing a specific task, and then experiences optimal consciousness when the desired goal is achieved (Pereira et al., 2022). It is a state of mind that describes an individual's enjoyment of an activity and involvement in the process (Jeon, Lee, & Jeong, 2017). From a technological perspective, Oinas-Kukkonen (2000) defines flow as an optimal experience that enhances consumer navigation and purchasing behavior on the web, and is predicted by consumer skills and difficulties, the feeling of being in control, and the perceived ease of use and usefulness of the system. As Hsu, Wu, and Chen (2012) reported, the study's results showed that perceived ease of use, usefulness, and regulatory fit positively affect flow. Our hypothesis regarding flow experience is as follows:

H6: Perceived usefulness has a positive impact on flow experience.

Curiosity is associated with a passion for acquiring and enriching knowledge, serving as a motivation that enables individuals to understand how to utilize technology and direct it in a way that supports their own goals (Alshurideh et al., 2024). Curiosity can be categorized as trait curiosity, which is related to individual attributes, and situational curiosity, which arises in particular setting (Berlyne, 1960, as cited in Wang & Zhang, 2023). Trait curiosity better reflects an individual's natural desire to understand the unknown than situational curiosity (Wang & Zhang, 2023). In our study, the curiosity construct measures users' openness to new, uncertain, challenging, or learning-oriented experiences and their willingness to utilize genAI-powered BI applications. A theoretical explanation by Dubey and Griffiths (2020) associates curiosity with the value of knowledge, which is a function of people's current understanding of a topic and the perceived usefulness of that topic and they stated that curiosity is aroused when a person perceives an opportunity to increase the value of their knowledge (as cited in Dubey, Griffiths, & Lombrozo, 2022). Later, Dubey, Griffiths, and Lombrozo (2022) demonstrate in their experiments that a person's curiosity and information-seeking behavior, which they create on their own, is influenced by the perceived usefulness of a scientific topic. The hypothesis regarding trait curiosity is as follows:

H7: Perceived usefulness has a positive impact on trait curiosity.

Trust is a mental state that can change not only when users experience the use of technology but also at any time before or after the technology experience (Ho & Cheung, 2024). According to Qin, Zhu, Jiang, Luo, and Huang (2024), previous studies on human-computer interaction propose that when users perceive a system or tool as technically proficient, it not only increases their belief in the system's outputs but also leads to an enhanced positive emotional bond with the technology. Studies by Murrar, Paz, Batra, and Yerger (2025) show a positive relationship between perceived usefulness and trust. In this study, the trust construct refers to the user's trust, belief, and confidence in the genAI-powered BI. The hypothesis regarding trust is as follows:

H8: Perceived usefulness has a positive impact on trust.

3.3 Stage 3: Outcome stage

The outcome stage is the users' behavioral willingness to engage with task-oriented AI tools (Yang, Luo, & Lan, 2022). In our study, users' feelings toward using genAI in secondary appraisal will determine their willingness to accept using genAI in BI applications.

Yang, Luo, and Lan (2022) introduced the concept of flow experience in their model, stating that when users perceive they can achieve a flow experience during interaction with task-oriented AI devices, they are more likely to believe that these devices can overcome their problems and help them achieve their goals. Jeon, Lee, and Jeong's (2017) study showed a positive relationship between flow experience and intention. Therefore, this research aims to measure the effect of users' flow experience when interacting with genAI in BI applications on their willingness to accept. The hypothesis is as follows:

H9: Flow experience has a positive impact on the willingness to accept genAI.

A user's curiosity about a technology is more likely to have behavioral intentions to accept the use of that technology. Acikgoz, Elwalda, and Oliveira (2023) stated that if consumers have a high level of curiosity, their desire to learn about that technology is high. Therefore, their intention to use it is high. Previous studies have shown that curiosity influences behavioral intentions (Acikgoz, Elwalda, & Oliveira, 2023; Perez, Prasetyo, Cahigas, Persada, Young, & Nadlifatin, 2023). By integrating trait curiosity into this model, we acknowledge the role of curiosity in encouraging users to accept genAI-powered BI applications. Our hypothesis is as follows:

H10: Trait curiosity has a positive impact on the willingness to accept genAI.

The construct of trust in perceptions regarding AI technologies is being examined due to the uncertainty in decision-making processes (Ho & Cheung, 2024). In the perception and acceptance of AI technologies, literature recommends that trust has a pivotal role (Choung, David, & Ross, 2022). The trust construct is crucial in predicting new technologies' acceptance in areas with low knowledge levels (Ho & Cheung, 2024). Unlike traditional technologies, where users have complete authority over the functions of a technology, AI's ability to automate processes poses risks and uncertainty for users (Choung, David, & Ross, 2022). Trust in technology is crucial for increasing the adoption and usage of genAI technology (Gupta & Mukherjee, 2024). When people trust the benefits of automation technology, they tend to accept it; when they do not, they are more likely to reject it (Lee & See, 2004). Rana et al. (2024) suggest that users' behavioral intention is positively and significantly associated with trust. Zhou and Lu's (2024) research revealed that trust significantly impacts users' adoption intentions for AI-generated content. Chi, Chi, Gursoy, and Nunkoo (2023) found that the trust construct is essential for developing behavioral intentions in AI robots, particularly among customers with a high risk-averse culture. Consequently, we advance the following hypothesis:

H11: Trust has a positive impact on the willingness to accept genAI.

3.4 Conceptual framework for the proposed study

The constructs and indicators for the model shown in Figure 16 were sourced from AIDUA, T-AIA, and different studies based on other AI adoption and acceptance studies. As previously detailed in developing our hypotheses, we explain the acceptance of genAI in BI applications using a three-stage model. In total, there are nine constructs of willingness to accept the use of genAI technologies, four of which (performance risk, conversational intelligence, continuous improvement, task-technology fit, and utilitarian motivation) are included in the primary appraisal stage. In contrast, the other four (perceived benefit, flow experience, feature curiosity, and trust in genAI are included in the secondary appraisal stage.

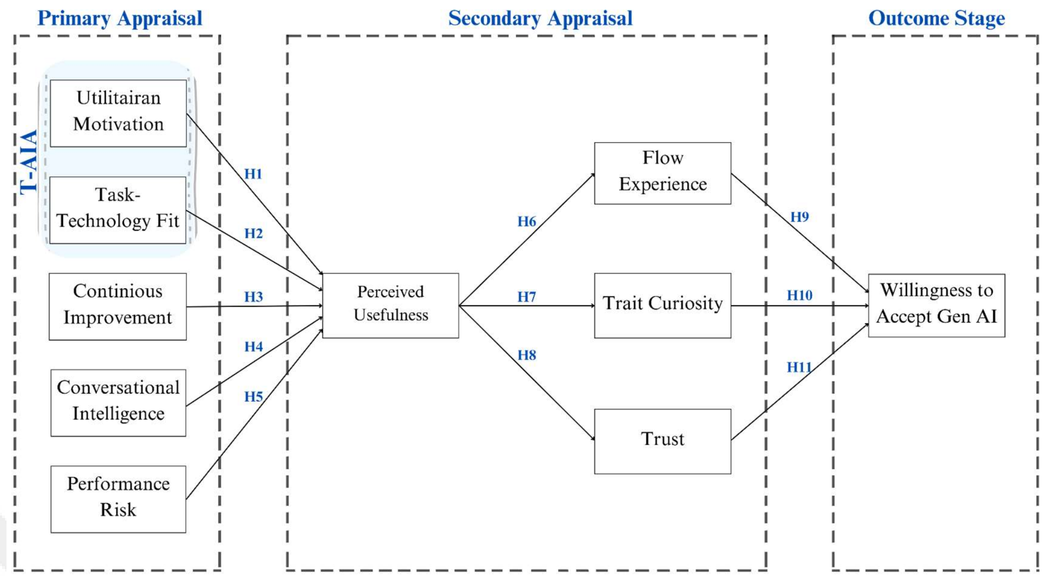

Figure 16. Conceptual framework

CHAPTER 4

RESEARCH METHODOLOGY

By providing empirical rigor through quantitative methods, actionable insights are derived from the data and used by preachers such as academics, practitioners such as industrialists, and policy makers such as the government (Lim, 2024). In this study, a quantitative research was conducted and a basis for the study was created by collecting and analyzing data through a survey.

4.1 Survey structure

A quantitative survey based on a literature review was prepared as part of the research methodology. Survey questions were collected from English sources and adapted for the study we aimed to conduct. To reach all users, the survey has been translated into both Turkish and English. Within the framework of the research, we aimed to obtain participants from various sectors, including finance, healthcare, transportation and logistics, technology, and many more. In this way, the aim is to analyze the perspectives of participants from different sectors regarding the application of genAI in BI. The survey consists of two parts.

The first part of the survey consisted of demographic questions designed to gain insight into the participants' knowledge and experience with BI tools and their frequency of use of genAI. We did not use these questions to test hypotheses directly. However, they were needed to understand and use the sample demographics in the data cleaning phase.

The second part of the questionnaire consists of questions that allow the model to be analyzed. The questions are a combination of questionnaires collected from different studies, according to the variables defined in our model, based on the literature review. A standardized questionnaire form, validated by other academic studies, is used by the researcher to reduce concerns about validity (Lucas, 1989). Additionally, all scales were maintained at the same level as those in the source studies from which the questions originated. In this study, performance risk (Prakash & Das, 2021), utilitarian motivation (Yang, Luo & Lan, 2022), task-technology fit (Yang, Luo & Lan, 2022), flow experience (Yang, Luo & Lan, 2022) factors are measured using a 7-point Likert scale according to the source from which they were taken. In the reference study of Yang and Lee (2024) and other studies referred to in these studies, where the continuous improvement structure was adopted, no details are given about the scale used for this structure. However, our research used it as a 7-point Likert scale. These constructs were rated on a scale of "1 = strongly disagree" to "7 = strongly agree". The remaining constructs are trait curiosity (Wang & Zhang, 2023), conversational intelligence (Ling et al., 2023), perceived usefulness (Gupta, 2024), trust in AI (Zhou & Lu, 2024), willingness to accept genAI (Skandali, Magoutas & Tsourvakas, 2024) measured using a 5-point Likert scale. The scores are rated "1 = strongly disagree" and "5 = strongly agree". All questions are included in the Appendix.

4.2 Data collection

Our survey aimed to identify the factors influencing the acceptance of genAI technology, which has gained significant business momentum over the past few years. For this purpose, target participants with specific knowledge and experience were identified, and the survey questions prepared via Google Forms were then shared via email and LinkedIn with these potential participants. The target audience comprises participants experienced in BI applications who aim to utilize or benefit from genAI technology in BI applications.

A pilot study was shared with the participants, and based on the feedback received, the survey's clarity, format, and length were adjusted to ensure that the items were interpreted and understood as intended (Lim, 2024). Spelling errors and misunderstandings were corrected after the pilot study.

An essential step in determining the validity and reliability of quantitative study is establishing an adequate sample size (Lim, 2024). Our study followed different methodologies to determine the minimum sample size. Firstly, according to the 10-times rule, the minimum sample size should be ten times the number of indicators used in the model (Barclay, Higgins, & Thompson, 1995). Therefore, since our study involves 10 variables, the target sample size is at least 100. According to Hair, Hollingsworth, Randolph, and Chong (2017), after using the ten-times rule as a rough guide for the minimum sample size, the sample size should be adjusted by considering the power analysis. In scientific research, making a false positive claim is often more serious than making a false negative claim, and since the implicit rule of thumb to avoid this is a = .05, a rule of .80 should be used for the desired power (Cohen, 1992). Following this, the minimum sample size calculated for the gamma-exponential method with power analysis in WarpPLS was 146.

Urbach and Ahlemann (2010) also suggested examining the common method bias in the data collection phase. Most researchers accept that common method variance, which arises from the method of measurement rather than the constructs captured by the measures, is a potential concern in behavioral research (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Common method variance arises when responses vary systematically due to using a common measurement approach in data collected from a single source (Fuller, Simmering, Atinc, & Babin, 2015). Harman's single-factor test is regarded as one of the most common techniques researchers use to identify the problem of common method variance (Podsakoff et al., 2003). According to Kock (2021), in partial least squares structural equation modeling (PLS-SEM), after creating a model with a single latent variable and performing a composite-based or factor-based analysis, the total variance explained is the average variance extracted (AVE) for the latent variable. If the AVE is greater than 0.5 according to both analysis results, it is stated that a common method bias exists in the dataset (Kock, 2021). According to Harman's single-factor test results, the AVE value was calculated to be 0.37. Since this value is less than 0.5, it can indicate that the dataset is not contaminated by common method bias (CMB) in the indicators.

Another alternative method for CMB analysis is the full collinearity test. Kock (2015) found that the full collinearity test successfully identified common method bias even in a model that passed standard convergent and discriminant validity assessment criteria. Additionally, before evaluating structural relationships, it is essential to examine linearity to confirm that it does not impact the regression results (Hair, Risher, Sarstedt, & Ringle, 2019). According to Kock (2017), a VIF value above 3.3 is recommended as an indicator of pathological collinearity and also as evidence that the model may be contaminated due to common method bias. On the other hand, Hair et al. (2017) recommend a VIF value smaller than 5. Details are given in Table 4 below:

Table 4. Full Collinearity VIF Values

UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
2.966	3.330	2.633	2.434	1.099	2.641	2.877	1.702	2.481	2.447

4.3 Data cleaning

As a result of the responses collected from online connection sharing via LinkedIn and email, the number of participants reached 149. Preliminary analysis revealed that one participant provided the same answer to each question. A widely recognized sign of correct answering of questions is straight lining, which is the tendency of survey respondents to give the same answers to successive questions (Reuning & Plutzer, 2020). Therefore, this participant's answers were eliminated. Also, it was mandatory to answer all questions that would affect the analysis, except for those for which we received more comments from participants later in the survey. Therefore, there is no data with missing answers.

Urbach and Ahlemann (2010) suggested examining nonresponse bias in the data collection phase for researchers. According to Urbach and Ahlemann (2010), after data collection, it can be verified that the responses of early and late respondents are not significantly different, allowing for the assessment of non-response bias. Therefore, in the analysis, we divided the survey responses into two groups according to their answer date. The sample sizes for these two groups were 115 for early responders and 33 for late responders. After performing t-tests to compare the differences regarding the demographic variables for early and late responses, the two-sided p value for gender, age, sector, education level, and role remained above 0.05. Only the value for experience and country remained below 0.05. It was stated by Cherubini and MacDonald (2021) that Cohen's $d = 0.2$ is small, $d = 0.5$ is medium, and $d = 0.8$ is large according to the effect sizes. Cohen's d value for the experience is below 0.5 and for the country is below 0.8.

CHAPTER 5

DATA ANALYSIS

This section will analyze the survey results. It aims to provide a general overview and sectoral and technological demographics of the participants. After the demographic analysis, the PLS-SEM results will be shared to analyze the theorized model.

5.1 Demographic analysis

5.1.1 General overview

Among the 148 participants included in the data analysis, 107 (72.3%) were male and 41 (27.7%) were female, with a majority of participants being male. Regarding age, 59.5% of the participants (n = 88) fell within the 18-30 age group. Participants aged 30-31 constituted the second-largest participation group (n = 47, 31.8%). The proportion of participants aged 41 and above was lower than that of the other groups. The most common level of education among the participants was a bachelor's degree (60.1%, n = 89). Additionally, the proportion of participants holding a master's and PhD degree was relatively high (n = 51, 34.5%). Most participants were employees with three to five years of experience (n = 49, 33.1%), while those with less than three years of experience constituted the second-largest group (n = 41, 27.7%). The general characteristics of the participants are shown in Table 5.

Table 5. General Overview

Variable	Category	n	n (%)
Gender	Male	107	72.3%
	Female	41	27.7%
Age	18-30	88	59.5%
	31-40	47	31.8%
	41-50	9	6.1%
	51-60	4	2.7%
Education Level	Secondary school or less	5	3.4%
	Bachelor's degree	89	60.1%
	Master's degree or PhD degree	51	34.5%
	Prefer not to say	3	2.0%
Experience	< 3 Years	41	27.7%
	3- 5 Years	49	33.1%
	6- 10 Years	28	18.9%
	11- 15 Years	14	9.5%
	> 15 Years	16	10.8%

More than half of the participants (n = 84, 56.8%) were from Türkiye. The second-highest number of participants came from India, at 12.2% (n = 18). Although most participants were from Türkiye and India, there were also participants from other countries, as indicated in Table 6. The survey was conducted entirely with participants the researcher could reach through LinkedIn and own network. Unlike Facebook and other more general social media platforms, LinkedIn is a platform that brings together professionals from different disciplines, allowing data collection to be targeted to a suitable social network (Dusek, Yurova, & Ruppel, 2015).

Table 6. Country-Based Distribution

Variable	Category	n	n (%)
Country	Turkey	84	56.8%
	India	18	12.2%
	United States	9	6.1%
	Spain	4	2.7%
	Iran	4	2.7%
	United Kingdom	3	2.0%
	Indonesia	3	2.0%
	China	3	2.0%
	Australia	2	1.4%
	Germany	2	1.4%
	Pakistan	2	1.4%
	France	2	1.4%
	United Arab Emirates	1	0.7%
	Myanmar (Burma)	1	0.7%
	Thailand	1	0.7%
	Holland	1	0.7%
	Sweden	1	0.7%
	Tunisia	1	0.7%
	Poland	1	0.7%
	Ghana	1	0.7%
	Jordan	1	0.7%
	Egypt	1	0.7%
	Brazil	1	0.7%
	Peru	1	0.7%

5.1.2 Sectoral demographics of participants

The sector with the highest participation rate is financial services (n=44, 29.7%). This is followed by technology, media, and telecommunications (n=36, 24.3%). 14.22% of the participants (n = 21) stated working in other sectors. Table 7 examines sectoral distribution.

Table 7. Sectoral Distribution

Variable	Category	n	n (%)
Sector	Financial Services	44	29.7%
	Technology, Media & Telecommunications	36	24.3%
	Other	21	14.2%
	Transportation & Logistics	15	10.1%
	Retail & Consumer Products	11	7.4%
	Construction & Engineering	8	5.4%
	Healthcare	6	4.1%
	Pharmaceuticals & Life Sciences	2	1.4%
	Industrial Manufacturing	2	1.4%
	Public Services	2	1.4%
	Automotive	1	0.7%

The data scientist, engineer, and analyst role group (n = 48, 32.4%) is the group that participated the most in the survey. Secondly, there are also many users in the role group we refer to as 'other' (n = 43, 29.1%). The third most participating group is the participants in the BI analyst/ engineer/ developer role group (n = 23, 15.5%). Details are given in Table 8 below:

Table 8. Role Group Distribution

Variable	Category	n	n (%)
Career	Data Scientist/ Engineer/ Analyst	48	32.4%
	Other	43	29.1%
	BI Analyst/ Engineer/ Developer	23	15.5%
	Manager	15	10.1%
	Project Manager	10	6.8%
	BI Product/Service User	6	4.1%
	Researcher/ Academic	3	2.0%

5.1.3 Technological demographics of participants

Microsoft Power BI is the most commonly used BI tool, with 55 respondents (37.2%). By adopting Power BI, organizations can cultivate a data-driven culture, enabling informed decisions and obtaining a competitive edge in today's data-driven world (Metre et al., 2023). After Power BI, most users (n = 25, 16.9%) use other BI tools not listed in the questionnaire. Eleven users (7.4%) use MicroStrategy and Tableau tools. The distribution of BI tools is shaped by the tools companies deem suitable for use, rather than by users' individual preferences. Details are given in Table 9 below:

Table 9. Distribution of BI Tools Used

Category	n	n (%)
Microsoft Power BI	55	37.2%
Other	25	16.9%
MicroStrategy	11	7.4%
Tableau	11	7.4%
SAP Business Objects	10	6.8%
Looker	8	5.4%
QlikSense	7	4.7%
Metabase	7	4.7%
Google Data Studio	4	2.7%
Zoho Analytics	4	2.7%
Oracle BI	3	2.0%
SAS Augmented Analytics & BI	1	0.7%
IBM Cognos Analytics	1	0.7%
Domo	1	0.7%

Another critical point in the analysis is the genAI usage rates of the users. Most users used genAI daily (n=46, 31.1%). Then, users who usually use (n = 39, 26.4%) and those who sometimes use (n = 37, 25.0%) are also the majority. The adoption rate of genAI among participants is relatively high compared to those who rarely use it (n=19, 12.8%) and plan to use it in the future (n=7, 4.75%). The results of our analysis provide evidence of the growing popularity of the use of genAI. Details are given in Table 10 below:

Table 10. GenAI Usage Frequency

Variable	Category	n	n (%)
GenAI Usage Frequency	Every day	46	31.1%
	Usually	39	26.4%
	Sometimes	37	25.0%
	Rarely	19	12.8%
	Plan to use in the future	7	4.7%

5.2 Validation of the model

PLS-SEM was selected as the analysis method for testing the structural model. The primary purpose of PLS-SEM is to maximize the variance explained in the dependent constructs and assess the data quality according to the measurement model specifications (Hair, Ringle, & Sarstedt, 2011). As suggested by Urbach and Ahlemann (2010), the study design and sample characteristics were carefully analyzed before selecting the PLS-SEM analysis method.

In terms of the research objective, according to the guidelines for making selection between CB-SEM and PLS-SEM by Hair, Ringle, and Sarstedt (2011), PLS-SEM should be selected if the aim is to estimate the underlying target constructs or to determine the underlying key determinants and if the research is exploratory or an expansion of an existing structural theory. PLS is more appropriate for theory development than theory testing (Urbach & Ahlemann, 2010). In addition, PLS methodology can be applied in a significant percentage of social science research when the research phenomenon is comparatively new or developing, and when theoretical models or measurements are not well-established (Chin & Newsted, 1999). This research proposed a combined model using the AIDUA and T-AIA theories. For this reason, the research model can be classified as an expansion of existing structural theories. Considering that the AIDUA and T-AIA theories are relatively new, PLS-SEM is more appropriate for the proposed research model regarding the research objective.

Regarding the structural model, according to Hair, Ringle, and Sarstedt's (2011) guidelines for choosing between CB-SEM and PLS-SEM, PLS-SEM is recommended for complex structural models with many constructs and indicators to be selected. The proposed model is a complex model with a large number of constructs.

According to Hair, Ringle, and Sarstedt (2011), PLS-SEM is recommended when the sample size is relatively small. PLS requires a smaller number of participants than other methods (Urbach & Ahlemann, 2010). Given the smaller number of participants (n = 148) used in this study, PLS-SEM is a suitable analysis method.

An appropriate software can be selected to analyze structural equation models by considering various criteria such as usability, methodological adequacy, statistical accuracy, documentation, and accessibility (Urbach & Ahlemann, 2010). According to Kock (2024), continuous feedback from all users, regardless of their knowledge of structural equation modeling (SEM), has contributed to WarpPLS version 8.0, which provides arguably the comprehensive feature set of any SEM software. Considering all these criteria, WarpPLS 8.0 was used to apply PLS-SEM analysis.

The model validation phase determines whether the measurement and structural models fulfill the quality benchmarks for experimental studies (Urbach & Ahlemann, 2010). According to Hair, Ringle, and Sarstedt (2011), PLS-SEM evaluation is typically conducted in a two-phase process that involves the separate analysis of the measurement and structural models.

5.2.1 Analysis of measurement model

The analysis of the measurement model step examines the reliability and validity of the measurements based on specific criteria related to the formative and reflective measurement model specification (Hair, Ringle, & Sarstedt, 2011). Urbach and Ahlemann (2010) recommend testing reflective measurement models for reliability (internal consistency reliability and indicator reliability) and validity (convergent validity and discriminant validity) by applying standard decision rules.

Different methods have been proposed in the literature to assess internal consistency reliability. Different methods have been proposed in the literature to assess internal consistency reliability. One of these methods is to assess Cronbach's alpha (CA) value greater than 0.7 (Urbach & Ahlemann, 2010; Hair et al., 2019). However, Cronbach's alpha is a less accurate measure of reliability because the items are not weighted when measured (Hair et al., 2019).

The second method to assess internal consistency reliability is composite reliability (Hair, Ringle, & Sarstedt, 2011; Urbach & Ahlemann, 2010). According to Hair et al. (2019), the range considered acceptable for reliability values in exploratory studies is 0.60-0.70, while the values considered satisfactory to good are between 0.70 and 0.90. If the reliability values are 0.95 and higher, this indicates the formation of unfavorable response patterns, such as straightlining, which can lead to inflated correlations between the error terms of the indicators (Hair et al., 2019). According to the analysis results in Table 11, the composite reliability coefficients and Cronbach's alpha coefficients are all higher than 0.7. The composite reliability coefficients of all latent variables are below 0.95.

For a convergent validity control, average variance extracted (AVE) should be greater than 0.50 (Urbach & Ahlemann, 2010). For an acceptable AVE, a value of 0.50 or higher suggests that the construct describes at least 50% of the variance of its elements (Hair et al., 2019). AVE is above the recommended threshold value for all latent variables.

Table 11. Internal Consistency, Reliability, and Convergent Validity

	Internal Consistency Reliability		Convergent Validity
Latent Variable	Composite Reliability Coefficients (>0.7)	Cronbach's Alpha Coefficients (>0.7)	AVE (>0.5)
UM	0.936	0.908	0.785
TTF	0.915	0.876	0.729
CIM	0.935	0.919	0.674
CI	0.921	0.903	0.565
PR	0.896	0.854	0.632
PU	0.947	0.932	0.747
FE	0.87	0.801	0.627
TC	0.874	0.83	0.502
TIA	0.926	0.879	0.806
WAT	0.939	0.921	0.719

Indicator reliability measures the degree to which the latent variable explains the variance in the indicators (Urbach & Ahlemann, 2010). Loadings of indicators should be at least 0.7 (Urbach & Ahlemann, 2010). In general, indicators with loadings between 0.40 and 0.70 should be considered for removal if removing the indicator would lead to an increase in composite reliability above the recommended threshold values (Hair, Ringle, & Sarstedt, 2011). Another rationale for removing indicators is how much they affect validity (Hair, Ringle, & Sarstedt, 2011). Only indicators with low loadings, 0.40 and below, should be removed from reflective scales (Hair, Ringle, & Sarstedt, 2011). Upon examining the factor loading table as a result of the analysis, no indicator is found to have a loading below 0.4. According to the study results, the value of some indicators in the TC and CI latent variables remains slightly below 0.7. Since we reached values above the threshold determined in the composite reliability or validity values, it was decided not to perform the removal process. The indicator loadings can be found in Appendix D.

Discriminant validity measures how empirically different a construct is from other constructs in the structural model (Hair et al., 2019). To measure discriminant validity, Hair, Ringle, and Sarstedt (2011) suggest two ways:

i. Fornell-Larcker Criterion: Each latent construct's AVE should be greater than the highest squared correlation of the construct with every other latent construct.
ii. The loadings of an indicator should be the highest compared to all its other cross-loadings.

Correlations among latent variables with square roots of AVEs were examined according to the Fornell-Larcker criterion. As shown in Table 12, the analysis results comply with this criterion.

Table 12. Correlations Among LVs with Square Roots of AVEs

	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
UM	0.886									
TTF	0.771	0.854								
CIM	0.388	0.524	0.821							
CI	0.43	0.567	0.615	0.751						
PR	-0.214	-0.241	-0.102	-0.055	0.795					
PU	0.552	0.57	0.641	0.586	-0.138	0.864				
FE	0.496	0.624	0.678	0.662	-0.105	0.619	0.792			
TC	0.462	0.433	0.451	0.46	-0.068	0.551	0.496	0.709		
TIA	0.379	0.508	0.648	0.673	-0.162	0.552	0.692	0.407	0.898	
WAT	0.574	0.514	0.596	0.44	-0.119	0.68	0.529	0.567	0.446	0.848

According to the 0.40–0.30–0.20 rule stated by Howard (2016), it is recommended that the primary factors of satisfactory variables should have values above 0.40, alternative factors should have values below 0.30, and there should be a difference of 0.20 between the primary and alternative factors. According to the analysis results, it is seen that the differences between the primary and alternative factor loadings of all indicators are greater than 0.2. For the results of the analysis, please check Appendix E.

There are also alternative methods to measure discriminant validity. Hair et al. (2019) stated that recent research suggests the Fornell-Larcker Criterion is unsuitable for assessing discriminant validity in terms of performance. Hair et al. (2017) advised authors to no longer rely on cross-loadings or Fornell-Larcker values, noting that they often significantly overestimate the presence of discriminant validity. Instead, Henseler, Ringle, and Sarstedt (2014) proposed the heterotraitmonotrait (HTMT) ratio of correlations as an alternative approach based on a multitrait-multimethod matrix to assess discriminant validity. The researcher can determine whether the HTMT value falls within the upper 95% confidence interval limit by examining whether it is less than 0.90 or 0.85 (Hair et al., 2019). When HTMT takes values less than 0.85, it is stated that there are conceptually different structures, and when it takes values less than 0.90, it is stated that there are conceptually similar structures (Hair et al., 2017). In the analysis, the value between all latent variables except one is below 0.85. The relationship between TTF and UM was classified as good with a value above 0.85 and below 0.9. Details are given in Table 13 below:

Table 13. HTMT Ratios (good if < 0.90, best if < 0.85)

	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
UM										
TTF	0.865									
CIM	0.427	0.586								
CI	0.475	0.637	0.678							
PR	0.242	0.278	0.142	0.156						
PU	0.597	0.631	0.693	0.639	0.156					
FE	0.581	0.74	0.791	0.778	0.177	0.714				
TC	0.53	0.51	0.52	0.54	0.21	0.625	0.614			
TIA	0.425	0.579	0.723	0.756	0.2	0.608	0.826	0.485		
WAT	0.628	0.574	0.654	0.481	0.156	0.736	0.615	0.648	0.498	

5.2.2 Analysis of structural model

The main evaluation conditions for the structural model, as outlined by Hair, Ringle, and Sarstedt (2011), are the magnitude and significance of the path coefficients and the R^2 values. The R^2 value should be considered the next step when linearity is not a concern (Hair et al., 2019). Since linearity was not a problem in this study and satisfactory values were obtained in the measurement model analysis, the structural model analysis stage proceeded. The average path coefficient, average R^2 value (ARS), average adjusted R^2 (AARS), average block VIF (AVIF) and average full collinearity VIF values are below the specified threshold values for the proposed model. It can be examined from Table 14.

Table 14. Model Fit and Quality Indices

Criterion	Values
Average path coefficient (APC)	0.320, $P<0.001$
Average R^2 (ARS)	0.408, $P<0.001$
Average adjusted R^2 (AARS)	0.400, $P<0.001$
Average block VIF (AVIF)	1.919, acceptable if <= 5, ideally <= 3.3
Average full collinearity VIF (AFVIF)	2.461, acceptable if <= 5, ideally <= 3.3

In addition, Q^2 and the coefficient of determination (R^2) of exogenous latent variables are given in Table 15. Q^2 values larger than zero are meaningful but have small predictive accuracy; Q^2 values around 0.25 have medium predictive accuracy, and 0.50 considerable predictive accuracy of the PLS path model (Hair et al., 2019). All Q Q^2 values are above the medium threshold value.

For R^2 values, approximately 0.670 is regarded as substantial, values around 0.333 are considered moderate, and values around 0.190 are regarded as weak (Hair et al., 2019). According to the analysis results, the R^2 values for PU and WAT are 0.593 and 0.428, respectively. These two values are between substantial and moderate. R^2 values were 0.395 for FE, 0.311 for TC, and 0.312 for TIA. These values are moderate, as they are approximately 0.333.

Table 15. Q^2 and R^2 Coefficients

Q^2 coefficients									
UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
					0.597	0.394	0.315	0.311	0.429
R^2 coefficients									
UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
					0.593	0.395	0.311	0.312	0.428

Various resampling methods, such as standard errors, can be chosen to calculate P values and related coefficients (Kock, 2024). The Stable3 method is the default in WarpPLS (Kock, 2024). The comparison in Table 16 below shows that the Stable3 method is the most accurate among the Stable3, Bootstrapping, and Jackknifing methods. For this reason, the application continued to use the default stable three methods provided by the application.

Table 16. Comparison of Resampling Methods

Stable3 P values										
	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
PU	<0.001	0.303	<0.001	0.001	0.375					
FE						<0.001				
TC						<0.001				
TIA						<0.001				
WAT							0.001	<0.001	0.046	
Bootstrapping P values										
	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
PU	<0.001	0.332	<0.001	0.003	0.337					
FE						<0.001				
TC						<0.001				
TIA						<0.001				
WAT							0.004	<0.001	0.126	

Jackknifing P values										
	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT
PU	<0.001	0.392	0.001	0.005	0.367					
FE						<0.001				
TC						<0.001				
TIA						<0.001				
WAT							0.012	<0.001	0.118	

Table 17 presents p-values, path coefficients, and effect sizes. According to these results, it is evident that Utilitarian Motivation (UM) ($\beta = 0.337$; $p < 0.001$), Continuous Improvement (CIM) ($\beta = 0.344$; $p < 0.001$), and Conversational Intelligence (CI) ($\beta = 0.242$; $p < 0.001$) constructs have statistically significant effects on Perceived Usefulness (PU). However, it is observed that Task-Technology Fit (TTF) ($\beta = 0.042$; $p = 0.303$) and Performance Risk (PR) ($\beta = 0.375$; $p = 0.026$) constructs do not have statistically significant effects on Perceived Usefulness (PU).

It is seen that Perceived Usefulness (PU) (β=0.628; $p < 0.001$) construct has statistically significant effects on Flow Experience (FE). The Perceived Usefulness (PU) construct ($\beta = 0.557$; $p < 0.001$) has statistically substantial effects on Trait Curiosity (TC). Perceived Usefulness (PU) ($\beta = 0.558$; $p < 0.001$) has a statistically significant impact on Trust in AI (TIA).

Flow Experience (FE) ($\beta = 0.238$; $p < 0.001$), Trait Curiosity ($\beta = 0.414$; $p < 0.001$), and Trust in AI constructs ($\beta = 0.135$; $p = 0.046$) have statistically significant effects on the willingness to accept the use of genAI (WAT).

Table 17. Structural Model Path Coefficients

Path	Path p-value	Path coefficient	Effect size
UM -> PU	<0.001	0.337	0.203
TTF -> PU	0.303	0.042	0.025
CIM -> PU	<0.001	0.344	0.221
CI -> PU	0.001	0.242	0.148
PR -> PU	0.375	0.026	0.005
PU -> FE	<0.001	0.628	0.395
PU -> TC	<0.001	0.557	0.311
PU -> TIA	<0.001	0.558	0.312
FE -> WAT	0.001	0.238	0.127
TC -> WAT	<0.001	0.414	0.241
TIA -> WAT	0.046	0.135	0.061

After all these analyses, we can formulate our theoretical framework that can be used to measure the willingness to accept genAI technology in BI applications, as shown in Figure 17 below:

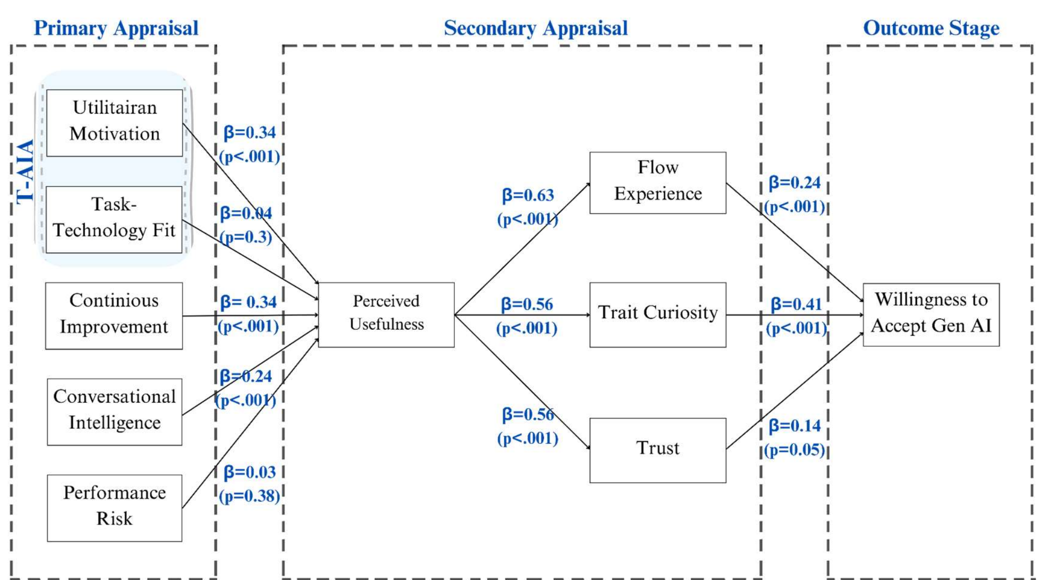

Figure 17. Model results

To provide further insight into the proposed model, the indirect effects of utilitarian motivation, task-technology fit, continuous improvement, conversational intelligence, and performance risk on flow experience, trait curiosity, and trust were estimated, as well as the indirect effects of perceived usefulness on willingness to accept the use of genAI. Results showed a significant positive indirect effect of utilitarian motivation on flow experience ($\beta = 0.212$, $p < 0.001$), trait curiosity ($\beta = 0.188$, $p < 0.001$), and trust in genAI ($\beta = 0.188$, $p < 0.001$) through the significant effect of perceived usefulness. Additionally, the analysis revealed a significant positive indirect effect of continuous improvement on flow experience ($\beta = 0.216$, $p < 0.001$), trait curiosity ($\beta = 0.192$, $p < 0.001$), and trust in genAI ($\beta = 0.192$, $p < 0.001$) through the significant effect of perceived usefulness. The indirect positive impact of conversational intelligence on flow experience ($\beta = 0.152$, $p = 0.004$) was also found to be significant, mediated by the considerable effect of perceived usefulness. Details are given in Table 18 below:

Table 18. Indirect Effect Coefficients

Path	Path p-value	Path coefficient	Effect size
UM -> FE via PU	<0.001	0.212	0.105
UM -> TC via PU	<0.001	0.188	0.087
UM -> TIA via PU	<0.001	0.188	0.071
TTF -> FE via PU	0.324	0.026	0.017
TTF-> TC via PU	0.343	0.023	0.010
TTF -> TIA via PU	0.342	0.024	0.012
CIM -> FE via PU	<0.001	0.216	0.147
CIM -> TC via PU	<0.001	0.192	0.086
CIM -> TIA via PU	<0.001	0.192	0.124
CI -> FE via PU	0.004	0.152	0.101
CI -> TC via PU	0.009	0.135	0.062
CI -> TIA via PU	0.009	0.135	0.091
PR -> FE via PU	0.389	0.016	0.002
PR -> TC via PU	0.401	0.014	0.001
PR -> TIA via PU	0.401	0.015	0.002

Also, the final results of the structural model, based on the survey data, are presented in Table 19. Nine out of eleven hypotheses in the model show significant relationships between the constructs and are statistically supported. All detailed analyses and questions regarding the model are presented in the Appendix B,C,D, and E.

Table 19. Model Results

Hypothesis	Results
H1: Utilitarian motivation has a positive impact on perceived usefulness	Supported
H2: Task-technology fit has a positive impact on perceived usefulness.	Not Supported
H3: Continuous improvement has a positive impact on perceived usefulness.	Supported
H4: Conversational intelligence has a positive impact on perceived usefulness.	Supported
H5: Performance risk has a negative impact on perceived usefulness.	Not Supported
H6: Perceived usefulness has a positive impact on flow experience.	Supported
H7: Perceived usefulness has a positive impact on trait curiosity.	Supported
H8: Perceived usefulness has a positive impact on trust.	Supported
H9: The flow experience has a positive impact on the willingness to accept genAI.	Supported
H10: Trait curiosity has a positive impact on the willingness to accept genAI.	Supported
H11: Trust has a positive impact on the willingness to accept genAI.	Supported

CHAPTER 6

DISCUSSIONS AND CONCLUSION

This section discusses and evaluates the study's results in more detail. It also assesses the study's contributions to the literature and practical implications. Finally, it presents the study's limitations and valuable insights for future studies based on this study.

6.1 Discussions

Based on the AIDUA and T-AIA theories, this study proposes a three-stage model to investigate the factors affecting users' acceptance of genAI in BI Applications. In line with the objectives sought to be achieved in this study, research questions were formulated to understand the current status of AI technology acceptance in the literature and the factors affecting users' behavioral intentions to adopt genAI technology in BI applications. The measurement and structural models were analyzed using the PLS SEM method via WarpPLS. The results showed that nine out of eleven hypotheses were supported.

In the primary appraisal phase, users first assessed the relevance of stimulus factors, including utilitarian motivation, task-technology fit, continuous improvement, conversational intelligence, and performance risk, and how these stimuli influenced or benefited users' values and beliefs about reaching their objectives. The findings revealed that users believe utilitarian motivation, continuous improvement, and conversational intelligence impact their values and beliefs about achieving their goals when encountering genAI in BI applications.

Among these, continuous improvement has the most significant coefficients. In terms of continuous improvement, genAI's ability to enhance itself by learning from past experiences and becoming more advanced, error-free, and competent over time contributes to its perceived usefulness. Continuous improvement should be considered, especially for genAI technologies, because the technology we are currently experiencing is still in its infancy. Although the errors and deficiencies encountered at this stage affect acceptance, the fact that this technology can continuously improve causes users to consider it still worth accepting. Although the previous study developed by Yang and Lee (2024) mainly focused on the impact of the continuous improvement feature of GenAI platforms on perceived authenticity, no academic studies were found regarding the potential impact of continuous improvement on perceived usefulness. Considering the importance of continuous improvement in GenAI, this study aims to address this gap by examining the impact of continuous improvement on perceived usefulness in this research. This finding extends the research of Yang and Lee (2024), who demonstrated the impact of the continuous improvement feature of GenAI platforms on perceived usefulness.

In addition, from the utilitarian motivation perspective, it was observed that users are more likely to focus on the benefits, functionality, or practicality that AI-powered BI will provide to them. Previous studies showed that utilitarian motivation is an essential determinant of perceived usefulness (Alam, Masukujjaman, & Ahmad, 2022; Kwon, 2015; Jo, 2023). In this study, according to utilitarian motivation, users evaluate genAI as an effective, helpful, functional, and practical tool for performing tasks in BI applications. Since individuals with utilitarian motivation focus more on the practical benefits of genAI-powered BI applications, they also evaluate the contribution of this service. Even with the self-service BI, users were still dependent on technical users to use BI. However, genAI-powered BI reduces the burden not only on non-technical users but also on technical users. The self-service technology provided by genAI-powered BI facilitates access to data, enabling organizations to make faster and smarter data-driven decisions that create real business value (Desai& Desai, 2025).

Lastly, the study findings show a positive relationship between conversational intelligence and perceived usefulness. When users interact with a system that incorporates conversational intelligence, the system’s ability to understand them quickly, recall previous questions, and generate contextually relevant and meaningful outputs enhances their confidence in the system's usefulness. For example, when a user requests the total sales for last year, the system’s ability to produce fast and meaningful outputs will support the user’s current goal, thereby increasing the perceived usefulness of the system. Although studies in the existing literature have discussed in detail that conversational intelligence is the main feature that shapes users' perceptions of AI assistants' intelligence and positively affects their intentions (Ling et al., 2024), the effect of conversational intelligence on perceived usefulness has not been sufficiently investigated. This study aims to fill this gap and reveal the effects of conversational intelligence on perceived usefulness in a different dimension.

An unexpected finding is that there is no direct relationship between task-technology fit and perceived usefulness. The relationship between these two variables is not statistically significant. From a theoretical perspective, this was expected to be a strong relationship. However, it can be interpreted that gen-AI-powered BI is insufficient for users because it is a relatively new technology. Although genAI is widely used in various applications, companies are taking time to transition to genAI in BI applications, which is progressing in a controlled manner. Integrating AI into workplace environments requires a more profound organizational transformation, where technical and adaptive challenges are intertwined and technological barriers are addressed (Tabata, Wildermuth, Bottomley, & Jenkins, 2025). Therefore, the growth rate of genAI technology may differ in terms of the growth rate on the companies' side and the competence it provides to the user. This difference should be considered, especially in applications such as BI, which are directly used in decision-making processes.

Another unexpected finding is that there is no direct relationship between performance risk and perceived usefulness. It also expected a strong relationship between these two constructs. Contrary to the findings observed in previous studies supporting the negative relationship between performance risk and perceived usefulness (Lee, Oh, & Moon, 2022; Wu & Ho, 2025; Kaushik & Kumar, 2017), the results in this study revealed that the performance risk of genAI-powered BI has no relationship on perceived usefulness. This means the absence of reliability concerns or error risk may not directly affect users' usability of BI powered by genAI. Even if the technology is immature and contains errors, it can still be helpful. In addition, the role of technical support providers in BI processes remains more essential than that of genAI. In this case, performance risk may reduce the impact of the evaluation criteria from the user perspective. Lastly, the extent to which AI is used in the decision-making process varies depending on the category of decision being made and how the decisions will impact the individuals and companies involved (Bonderud, 2025). At this maturity level, genAI is used more to facilitate processes, so users may not be as sensitive as expected in risk assessment.

In the secondary appraisal phase, a positive relationship was found between perceived usefulness and flow experience, trait curiosity, and trust in genAI. In this phase, users produced a comprehensive review of using genAI-powered BI applications. The findings indicated that users produced a second evaluation of the emotional state after evaluating the stimulus in the first stage. This will further affect their emotional state. As the results show, when users perceive higher levels of usefulness, they are more likely to experience a flow state, exhibit trait curiosity, and trust in genAI.

According to the research findings, a significant and positive relationship exists between perceived usefulness and the flow experience. This result aligns with the findings found in prior research (Hsu, Wu, & Chen, 2012), which indicated that the perceived usefulness has a positive impact on the flow experience. Users can simplify their business operations using AI-powered BI, creating a smooth experience where they can quickly extract meaning from data without requiring technical expertise. This experience is optimal, as predicted by the user's sense of being in a flow state and the system's perceived usefulness. For example, users' perception of Gen-AI-powered BI applications as applicable indicates that they experience a state where they lose track of time and become entirely immersed in the flow while interacting with the applications.

The results showed that perceived usefulness positively affects trait curiosity. This finding aligns with the previous study by Dubey, Griffiths, and Lombrozo (2022), which emphasized that a user's self-generated curiosity and information-seeking behavior are influenced by the perceived usefulness of a scientific topic. Users who perceive genAI-powered BI as applicable become more curious about this technology. In other words, as users find genAI technology useful in BI processes, this technology helps users see it as an experience that challenges their thinking and seeks new experiences.

According to the study's findings, perceived usefulness positively impacts trust in genAI. If users perceive genAI-powered BI applications as applicable, they develop a sense that the system is reliable over time. Especially in task-oriented tasks, the usefulness provided by AI-powered BI enables users to complete their assignments and work successfully within a tight timeframe. They tend to place more trust in genAI's reliability and credibility. These findings align with the prior study, which shows a positive relationship between perceived usefulness and trust (Murrar, Paz, Batra & Yerger, 2025).

In the final stage, it was revealed that users' feelings, such as flow experience, trait curiosity, and trust in using genAI, as determined in the secondary evaluation, influenced their willingness to accept genAI in BI applications. If users experience flow when interacting with genAI-powered BI applications, they are likely to believe that the service can help them achieve their goals and solve problems. Users experiencing flow indicate that when interacting with genAI-powered BI, users are immersed in the interaction and feel that time passes very quickly. This finding is consistent with the previous study by Jeon, Lee, and Jeong (2017), which shows a positive relationship between flow experience and willingness to accept.

Trait curiosity emerged as a strong antecedent of willingness to accept in the model. When customers have a better experience with AI-powered BI applications, their desire to adopt them increases. Accordingly, this study's results reveal that the curiosity a user feels for a technology is more likely to have behavioral intentions towards accepting the use of that technology. This finding is consistent with the results of previous studies showing that curiosity affects behavioral intentions (Acikgoz et al., 2023; Perez et al., 2023).

Additionally, as user curiosity increases, the rate of willingness to accept also rises. Finally, the acceptance rate is high as users' trust in genAI increases. Increased user trust in genAI has emerged as an essential antecedent of acceptance. Literature has shown that trust is critical in the perception and acceptance of AI technologies (Choung, David & Ross, 2022; Rana et al., 2024; Zhou & Lu, 2024; Chi et al., 2023). This study shows that when users trust the output they get from genAI-powered BI applications, they tend to accept it.

6.2 Theoretical contribution

This study provides some valuable insights to the literature. To the best of our knowledge, there is no existing literature on the acceptance of genAI in BI applications. Therefore, this study will contribute to the literature on the acceptance of genAI in BI applications.

During the literature review, more traditional models that ignored AI features were used for AI and genAI acceptance. This study identified the most critical antecedents in users' willingness to use genAI-powered BI applications and tested the interrelationships between these antecedents. While examining the antecedents of this study, instead of traditional AI acceptance and adoption models, AIDUA and T-AIA theories that also take into account the features of AI and measure acceptance step by step were used. However, while adapting these models to this study, the effects of both BI features and other antecedents thought to affect genAI acceptance were measured. For example, the trait curiosity factor, which was not found in the secondary appraisal of the main models, was also added to this model. This study showed that perceived usefulness on the user's side effects trait curiosity. In this context, it was aimed to contribute to the literature by going one step further by using models from the existing literature.

The model proposed in this study suggests that conversational intelligence and continuous improvement effectively determine users' acceptance of genAI in the primary appraisal. Although these premises have not been extensively evaluated in previous academic studies, they are essential in assessing genAI technology. At an earlier stage in the development of technology and AI studies, the self-improvement of systems or conversational interaction with them was not as prominent as in genAI. These premises surpass the existing technology acceptance literature by considering the specific features of genAI in the interaction between users and genAI.

6.3 Practical implications

GenAI is now widely used by users in different areas of business life. Before integrating these innovations into their systems, businesses should understand the factors that affect users' acceptance of genAI. The practical implications of this study, which uses the AIDUA and T-AIA models for AI-powered BI applications, are as follows: First, utilitarian motivation, continuous improvement, conversational intelligence, perceived usefulness, flow experience, trait curiosity, and trust are essential antecedents that increase customers' intention to use genAI-powered BI. Among these, continuous improvement is of critical importance. The belief that the technology will continuously improve itself in the service provided to users increases its use. Investing in these technologies increases the investment rate due to their self-improvement feature.

The second factor is conversational intelligence, which contributes to users' intention. The quality of the conversational interaction that the user establishes with the system first provides the perceived usefulness of the system and then enables them to create trait curiosity. Therefore, product providers and companies should more clearly introduce the advantages of these services in conversational interfaces. At the same time, improvements in user interaction with conversational interfaces will lead to higher user satisfaction. Investment in conversational intelligence will support user acceptance with a higher return on investment.

Thirdly, perceived usefulness is a relevant factor that indirectly affects customers' intention to accept genAI-powered BI through the effect of the flow experience. When using genAI, if users perceive that genAI can complete tasks that match with their initial assessments, they are expected to be more inclined to continuously use AI devices to receive service. Therefore, organizational leaders need to improve the service capability of genAI applications and enable users to interact with genAI by experiencing flow experiences. As different industries accept genAI technologies in BI applications, practitioners should proactively drive this evolving technology. This includes continuous improvement of genAI-powered BI applications and focusing on generating user-satisfying outputs with conversational intelligence that enhances user experiences and increases acceptance. The emphasis should also be extended to creating a flow experience, building trust, and developing a curiosity trait.

6.4 Limitations of the study and future studies

One limitation of this study is the small sample size. Our dataset consists of 148 responses. As mentioned in Section 4.2, a sufficient number of users were reached, but reaching additional users within the limited time frame was difficult. This study can be replicated in future studies with more participants and evaluated from different perspectives of non-technical and technical users.

The current study was conducted during the early stages of the development of genAI technology. Although this study provides valuable insights, the current maturity level of genAI technology may limit users' ability to evaluate perceived usefulness. Longitudinal study designs that re-evaluate the relationships between variables and how these antecedents have evolved will provide more accurate results.

In addition, future researchers can conduct qualitative studies to examine antecedents, such as current perceived usefulness, trust in AI, and flow experience, or other antecedents not included in this study. Researchers can uncover users' cognitions, feelings, and in-depth cognitive evaluations of the antecedents through in-depth interviews or focus groups.

BI applications are critical in companies' decision-making processes. Unlike other studies on accepting genAI or AI, the risk structure should be evaluated in more detail when evaluating genAI-powered BI. Although there was no significant relationship between performance risk and acceptance in this study, the Enron scandal encountered during the literature review showed that the risk factor should be evaluated in more detail for companies when the issue is decision-making. Instead of establishing a functional internal audit mechanism, Enron ignored suspicious accounting practices and fraudulent financial reporting by receiving external support to fulfill the internal audit function. In genAI-powered BI, instead of fraudulent reporting, outputs that do not truly reflect the data set may occur due to the hallucinatory feature of AI. Therefore, the following questions may guide future research:

- Although genAI's advantages in user acceptance and continuous improvement can minimize errors, to what extent should we trust genAI in BI in decision-making processes?
- Will users choose to rely 100% on the genAI-powered BI in their processes, or will a process that includes a switching mechanism to decide between humans and genAI be required?

Considering all these issues, the risk factor can be evaluated more carefully in future studies. The switching mechanism between humans and genAI can be included in the final stage for future research.

APPENDIX A

ETHICS COMMITTEE APPROVAL OF THE SURVEY

T.C.
BOĞAZİÇİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (Sbinarek)

2025 AİLE YILI

Sayı : E-84391427-050.04-222604 27.02.2025
Konu : 2025-16T Kayıt Numaralı Başvurunuz Hakkında

Sayın Doç. Dr. Nazım TAŞKIN

Tez danışmanlığını yürüttüğünüz öğrenciniz Seçil Bertiz Taş'ın " İş Zekasında Üretken Yapay Zekanın Kabulünü Etkileyen Faktörlerin İncelenmesi" başlıklı projesi ile Boğaziçi Üniversitesi Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (SBİNAREK)'e yaptığınız 2025-16T kayıt numaralı başvuru 17.02.2025 tarih ve 2025/02 sayılı kurul toplantısında incelenmiş ve projeye etik onay verilmesi uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya on-line olarak katılımıyla ve oybirliği ile alınmıştır. Onay mektubu tüm üyeler adına Komisyon Başkanı tarafından e-imzalanmıştır. Bilgilerinizi rica ederiz.

Saygılarımızla,

Dr. Öğr. Üyesi Işıl ERDUYAN
Kurul Başkanı

APPENDIX B
DEMOGRAPHIC QUESTIONS

- Your Gender: (Open text)
- Your Age: (Open text)
- Please select the generative Artificial Intelligence (genAI) production activity of the business intelligence applications we consider when providing information in this survey.
    - Options: (Financial Services), (Technology, Media & Telecommunications), (Energy, Infrastructure & Natural Resources), (Retail & Consumer Products), (Automotive), (Industrial Manufacturing), (Construction & Engineering/ Healthcare), (Transportation & Logistics), (Private Equity), (Public Services), (Pharmaceuticals & Life Sciences), (Other)

- Please indicate the country the organization that uses the business intelligence product/service that you will consider when answering the questions in this survey is located.
    - Options: Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Costa Rica, Côte d'Ivoire, Croatia, Cuba, Cyprus, Czechia (Czech Republic), Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Eswatini,

Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, North Korea, South Korea, Kosovo, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Micronesia, Moldova, Monaco, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Palau, Panama, Palestine, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Sudan, Spain, Sri Lanka, Sudan, Suriname, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Vatican City, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe, Other

- What is the size of your company?
    - Options: (< 100 Employees), (100- 500 Employees), (501- 2000 Employees), (> 2000 Employees)
- What is the highest level of education you have completed?
    - Options: (Less than high school), (High school or equivalent), (Secondary school), (Bachelor's degree), (Master's degree), (PhD degree), (Prefer not to say)
- What is your current position in the company you work for?
    - Options: (Business Intelligence Product/Service User), (Data Scientist/ Engineer/ Analyst), (Business Intelligence Analyst/ Engineer/ Developer), (Project Manager), (Manager (Department Manager, Director and Senior Manager)), (Researcher/ Academic), (Other)
- Please indicate how many years of work experience you have.
    - Options: (< 3 Years), (3- 5 Years), (6- 10 Years), (11- 15 Years), (> 15 Years)
- How often do you use gen AI in your business intelligence process?
    - Options: Rarely, Sometimes, Usually, Every day, Plan to use in the future
- Which business intelligence tool do you use the most?
    - Clear Analytics, Domo, Dundas BI, Google Data Studio, IBM Cognos Analytics, Looker, Metabase, MicroStrategy, Microsoft Power BI, Oracle BI, QlikSense, SAP Business Objects, SAS Augmented Analytics & Business Intelligence, Sisense, Tableau, TIBCO Spotfire, Yellowfin BI, Zoho Analytics, Other

APPENDIX C

INDICATORS FOR THE MODEL

Construct	Item	Statement	Scale	Source
Performance Risk	PR1	I am concerned about whether the use of genAI technology in business intelligence processes will perform as well, as it is supposed to.	5-point Likert	Prakash & Das (2021)
	PR2	The thought of using genAI technology in business intelligence processes causes me to be concerned about how reliable its service will be.		
	PR3	I am concerned that using genAI technology in business intelligence processes will not provide the level of benefits I would be expecting.		
	PR4	I am worried about the errors that would be caused by using genAI technology in business intelligence processes.		
	PR5	I believe the emerging genAI technology in business intelligence processes is not technically mature so far.		
Trait Curiosity	TC1	My willingness to use genAI technology in business intelligence processes is high.	5-point Likert	Wang & Zhang (2023)
	TC2	I actively look for all possible information when faced with a new situation.		
	TC3	Everywhere I go, I look for new things or experiences.		
	TC4	I see difficult situation as opportunity to grow and learn.		
	TC5	I like doing things that are frightening.		
	TC6	I'm always looking for experiences that challenge the way I think.		
	TC7	I prefer to have work that is unpredictable on a daily basis.		

Construct	Item	Statement	Scale	Source
Conversational Intelligence	CI1	GenAI technology understands me well in business intelligence processes.	5-point Likert	Ling, Tussyadiah, Liu & Stienmetz (2023)
	CI2	The genAI technology in business intelligence applications is intelligent.		
	CI3	The genAI technology in business intelligence applications remembers what I asked previously.		
	CI4	The genAI technology in business intelligence applications is smart.		
	CI5	The genAI technology in business intelligence applications recognizes the context of the conversation.		
	CI6	The genAI technology in business intelligence application acts like human.		
	CI7	The conversation with the genAI technology in business intelligence application flows smoothly.		
	CI8	The conversation with the genAI technology in business intelligence application flows naturally.		
	CI9	The genAI technology in business intelligence application is proactive in delivering information.		
Utilitarian Motivation	UM1	Using genAI technology in business intelligence applications for your business processes is effective.	7-point Likert	Yang, Luo & Lan (2022)
	UM2	Using genAI technology in business intelligence applications for your business processes is helpful.		
	UM3	Using genAI technology in business intelligence applications for your business processes is functional.		

Construct	Item	Statement	Scale	Source
Utilitarian Motivation	UM4	Using genAI technology in business intelligence applications for your business processes is practical.	7-point Likert	Yang, Luo & Lan (2022)
Task-Technology Fit	TTF1	In helping me to perform the assigned tasks, the use of genAI technology in business intelligence processes is very adequate.	7-point Likert	Yang, Luo & Lan (2022)
	TTF2	In helping me to perform the assigned tasks, the use of genAI technology in business intelligence processes is very compatible with the task.		
	TTF3	In helping me to perform the assigned tasks, the use of genAI technology in business intelligence processes is very helpful.		
	TTF4	In helping me to perform the assigned tasks, the use of genAI technology in business intelligence processes is made the task very easy.		
Perceived Usefulness	PU1	Using genAI technology in business intelligence processes will help me to accomplish my business tasks more quickly.	5-point Likert	Gupta (2024)
	PU2	Using genAI technology in business intelligence processes will help me to improve my performance at work.		
	PU3	Using genAI technologies will help me to improve my productivity at job.		
	PU4	Using genAI technology in business intelligence processes will help me to improve my effectiveness on the job.		
	PU5	Using genAI technology in business intelligence processes will help me to make it easier to do my job.		
	PU6	I find genAI technology useful in business intelligence processes.		

Construct	Item	Statement	Scale	Source
Continuous Improvement	CIM1	The genAI technology in business intelligence can learn from past experience.	7-point Likert	Yang & Lee (2024)
	CIM2	The genAI technology in business intelligence applications is enhanced through learning.		
	CIM3	After a period of use, the genAI technology in business intelligence performance is getting better and better.		
	CIM4	I can feel the genAI technology in business intelligence is constantly upgrading.		
	CIM5	The genAI technology in business intelligence fixes previous errors.		
	CIM6	I feel that the genAI technology in business intelligence applications is getting more and more advanced.		
	CIM7	The function of the genAI technology in business intelligence applications has been enhanced.		
Flow Experience	FE1	When I was interacting with genAI technology in BI application, I felt totally captivated.	7-point Likert	Yang, Luo & Lan (2022)
	FE2	When I was interacting with genAI technology in BI application, time seemed to pass very quickly.		
	FE3	When I obtained assistance from GenAI technology in BI application, nothing seemed to matter to me.		
	FE4	When I obtained customer service from GenAI technology in BI application, I was full involved.		

Construct	Item	Statement	Scale	Source
Trust	TIA1	GenAI technology in business intelligence processes is reliable.	5-point Likert	Zhou & Lu (2024)
	TIA2	GenAI technology in business intelligence processes is credible.		
	TIA3	Overall, I can trust genAI technology in business intelligence processes.		
Willingness to Accept GenAI	WIL1	I am willing to download the genAI for business intelligence.	5-point Likert	Skandali, Magoutas & Tsourvakas (2024)
	WIL2	I will feel happy to interact with the genAI application in business intelligence.		
	WIL3	I am likely to interact with the genAI in business intelligence.		
	WIL4	I plan to use the genAI in business intelligence in the next 6 months.		
	WIL5	I intend to use the genAI in business intelligence in the next 6 months.		
	WIL6	I predict I will use the genAI in business inteligence in the next 6 months.		

APPENDIX D

CROSS LOADINGS

	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT	P value
UM1	0.91	0.06	-0.18	-0.02	-0.02	0.05	-0.07	0.02	0.15	0.19	<0.001
UM2	0.91	-0.02	0.01	-0.08	0.03	0.14	0.03	0.10	-0.12	-0.08	<0.001
UM3	0.91	-0.11	0.12	-0.10	0.00	-0.04	0.02	0.03	0.02	-0.16	<0.001
UM4	0.82	0.08	0.06	0.22	-0.01	-0.16	0.02	-0.17	-0.06	0.06	<0.001
TTF1	-0.20	0.84	-0.07	-0.08	0.03	-0.11	0.08	-0.13	0.02	0.19	<0.001
TTF2	0.06	0.89	-0.07	0.17	-0.04	0.01	0.12	-0.06	-0.06	-0.02	<0.001
TTF3	0.17	0.87	-0.06	-0.13	0.02	0.11	-0.10	0.13	0.05	-0.12	<0.001
TTF4	-0.04	0.82	0.21	0.04	-0.01	-0.01	-0.10	0.06	0.00	-0.05	<0.001
CIM1	0.12	-0.13	0.77	-0.03	0.10	-0.33	-0.01	0.12	0.39	0.09	<0.001
CIM2	0.14	-0.01	0.79	-0.03	0.02	-0.10	-0.26	0.02	0.35	-0.09	<0.001
CIM3	0.04	-0.05	0.87	0.03	-0.07	0.13	-0.10	-0.17	-0.10	-0.08	<0.001
CIM4	-0.26	0.31	0.83	-0.17	-0.01	0.24	0.19	-0.06	-0.35	-0.02	<0.001
CIM5	-0.07	-0.06	0.81	0.21	0.05	-0.14	0.20	-0.06	-0.13	0.08	<0.001
CIM6	-0.11	0.00	0.84	-0.06	-0.12	0.15	0.17	0.06	-0.21	0.10	<0.001
CIM7	0.15	-0.06	0.83	0.05	0.04	0.01	-0.19	0.09	0.10	-0.07	<0.001
CI1	-0.23	0.33	-0.18	0.75	-0.06	-0.13	-0.12	0.11	-0.01	0.26	<0.001
CI2	-0.29	0.31	-0.18	0.73	-0.09	0.08	0.36	0.07	0.06	-0.03	<0.001
CI3	-0.03	-0.12	0.17	0.65	-0.06	-0.07	-0.19	0.27	-0.06	-0.10	<0.001
CI4	0.26	-0.14	0.20	0.76	-0.10	0.12	-0.32	0.00	0.18	-0.25	<0.001
CI5	-0.02	0.04	0.10	0.76	-0.07	0.29	-0.30	0.13	0.07	-0.22	<0.001
CI6	-0.17	0.07	-0.07	0.75	0.16	-0.13	0.08	-0.13	0.27	0.15	<0.001
CI7	0.32	-0.28	-0.01	0.82	0.05	0.05	0.07	-0.11	-0.16	-0.03	<0.001
CI8	0.21	-0.27	0.04	0.81	0.05	-0.06	0.16	-0.15	-0.21	0.07	<0.001
CI9	-0.11	0.11	-0.05	0.73	0.11	-0.15	0.24	-0.14	-0.11	0.14	<0.001
PR1	-0.21	0.24	-0.17	0.07	0.78	-0.11	-0.08	0.19	0.13	0.12	<0.001
PR2	0.14	-0.12	0.00	0.02	0.79	-0.19	-0.04	0.08	0.28	-0.03	<0.001
PR3	-0.17	0.07	-0.03	-0.13	0.82	0.06	0.04	-0.10	0.05	0.07	<0.001
PR4	0.01	0.07	0.06	-0.01	0.84	0.09	0.05	-0.06	-0.22	-0.08	<0.001
PR5	0.26	-0.28	0.15	0.07	0.74	0.15	0.01	-0.12	-0.24	-0.08	<0.001

	UM	TTF	CIM	CI	PR	PU	FE	TC	TIA	WAT	P value
PU1	-0.13	0.01	0.22	0.18	-0.04	0.79	-0.11	0.11	-0.19	-0.23	<0.001
PU2	0.02	-0.01	-0.06	0.05	0.05	0.91	0.04	-0.01	0.03	-0.01	<0.001
PU3	-0.18	0.02	-0.13	-0.01	0.03	0.88	0.10	0.06	-0.03	0.13	<0.001
PU4	0.18	-0.12	-0.16	-0.08	0.07	0.88	0.05	0.02	0.31	-0.01	<0.001
PU5	0.04	0.01	0.14	-0.02	-0.07	0.87	-0.10	-0.11	-0.14	-0.06	<0.001
PU6	0.05	0.10	0.02	-0.11	-0.06	0.85	0.01	-0.06	0.00	0.14	<0.001
FE1	0.06	-0.12	0.13	-0.01	-0.14	0.15	0.78	0.08	-0.13	-0.01	<0.001
FE2	-0.07	0.05	0.22	-0.11	0.07	0.06	0.79	0.07	-0.19	-0.15	<0.001
FE3	0.23	-0.29	-0.16	0.11	0.05	-0.16	0.74	-0.26	0.27	0.02	<0.001
FE4	-0.19	0.32	-0.19	0.01	0.03	-0.05	0.85	0.09	0.05	0.13	<0.001
TC1	0.39	-0.23	0.14	-0.23	-0.06	0.01	0.25	0.61	0.05	0.23	<0.001
TC2	0.44	-0.24	0.18	0.06	-0.10	0.03	-0.34	0.72	-0.04	-0.08	<0.001
TC3	0.11	-0.01	0.10	-0.13	0.02	0.16	0.00	0.87	-0.06	0.01	<0.001
TC4	0.08	-0.17	0.12	0.09	-0.18	-0.09	-0.04	0.67	-0.10	-0.17	<0.001
TC5	-0.39	0.25	-0.24	0.07	0.03	0.10	0.03	0.64	0.09	-0.12	<0.001
TC6	-0.21	0.09	-0.06	0.04	0.14	-0.01	-0.01	0.78	-0.09	-0.01	<0.001
TC7	-0.45	0.30	-0.28	0.12	0.13	-0.27	0.18	0.65	0.20	0.16	<0.001
TIA1	-0.03	-0.04	-0.03	-0.03	-0.02	0.00	0.08	0.04	0.89	-0.09	<0.001
TIA2	0.02	-0.04	0.03	0.00	0.02	0.03	0.05	-0.01	0.90	0.03	<0.001
TIA3	0.01	0.09	0.01	0.03	0.00	-0.03	-0.13	-0.04	0.90	0.06	<0.001
WAT1	0.22	-0.25	0.41	-0.24	-0.05	0.09	-0.04	0.01	0.10	0.77	<0.001
WAT2	0.08	-0.05	0.32	-0.13	-0.09	0.11	0.12	-0.10	-0.13	0.79	<0.001
WAT3	0.17	-0.20	0.03	-0.14	0.06	0.17	-0.06	0.12	0.17	0.87	<0.001
WAT4	-0.14	0.24	-0.25	0.11	0.00	-0.14	-0.04	0.08	-0.01	0.89	<0.001
WAT5	-0.14	0.10	-0.18	0.17	-0.02	-0.03	0.03	-0.09	-0.15	0.90	<0.001
WAT6	-0.14	0.11	-0.24	0.17	0.09	-0.19	-0.01	-0.03	0.02	0.87	<0.001

APPENDIX E

PRIMARY FACTOR AND ALTERNATIVE FACTORS DIFFERENCES

	(1) Max Indicator Loadings	(2) Second Max Loadings Value among Other Indicators	Difference btw (1) and (2)	0,2 control
UM1	0,906	0,185	0,721	Yes
UM2	0,907	0,137	0,77	Yes
UM3	0,905	0,118	0,787	Yes
UM4	0,823	0,218	0,605	Yes
TTF1	0,844	0,186	0,658	Yes
TTF2	0,887	0,17	0,717	Yes
TTF3	0,865	0,17	0,695	Yes
TTF4	0,819	0,208	0,611	Yes
CIM1	0,772	0,392	0,38	Yes
CIM2	0,785	0,353	0,432	Yes
CIM3	0,869	0,133	0,736	Yes
CIM4	0,83	0,307	0,523	Yes
CIM5	0,814	0,214	0,6	Yes
CIM6	0,842	0,174	0,668	Yes
CIM7	0,831	0,149	0,682	Yes
CI1	0,754	0,329	0,425	Yes
CI2	0,734	0,364	0,37	Yes
CI3	0,653	0,267	0,386	Yes
CI4	0,756	0,257	0,499	Yes
CI5	0,756	0,289	0,467	Yes
CI6	0,747	0,267	0,48	Yes
CI7	0,815	0,318	0,497	Yes
CI8	0,811	0,208	0,603	Yes
CI9	0,726	0,235	0,491	Yes
PR1	0,78	0,241	0,539	Yes
PR2	0,793	0,282	0,511	Yes
PR3	0,819	0,074	0,745	Yes
PR4	0,84	0,087	0,753	Yes
PR5	0,74	0,255	0,485	Yes
PU1	0,789	0,219	0,57	Yes
PU2	0,913	0,067	0,846	Yes
PU3	0,882	0,133	0,749	Yes
PU4	0,882	0,306	0,576	Yes
PU5	0,867	0,142	0,725	Yes
PU6	0,848	0,142	0,706	Yes
FE1	0,782	0,148	0,634	Yes

FE2	0,791	0,221	0,57	Yes
FE3	0,741	0,274	0,467	Yes
FE4	0,85	0,317	0,533	Yes
TC1	0,607	0,391	0,216	Yes
TC2	0,716	0,438	0,278	Yes
TC3	0,872	0,164	0,708	Yes
TC4	0,667	0,123	0,544	Yes
TC5	0,639	0,253	0,386	Yes
TC6	0,778	0,143	0,635	Yes
TC7	0,646	0,301	0,345	Yes
TIA1	0,886	0,075	0,811	Yes
TIA2	0,902	0,067	0,835	Yes
TIA3	0,904	0,086	0,818	Yes
WAT1	0,766	0,406	0,36	Yes
WAT2	0,788	0,32	0,468	Yes
WAT3	0,868	0,174	0,694	Yes
WAT4	0,888	0,24	0,648	Yes
WAT5	0,899	0,172	0,727	Yes
WAT6	0,87	0,166	0,704	Yes

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