
AI206X Degree Project in Real Estate and Construction Management

Second Cycle, 30 credits

# Acceptance and Applications of Generative AI in Property Management

A Study Exploring Opportunities and Challenges

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## Abstract

Digitization and Artificial Intelligence are currently one of the most discussed topics in the real estate industry and are claimed to represent a fundamental revolution rather than a short-term trend or hype. Historically, the real estate industry has been slow to adopt new technology, including traditional analytical AI. However, since OpenAI launched ChatGPT in November 2022, there has been a resurgence of interest in the potential of large language models and more specifically generative AI. The new attention has sparked great enthusiasm for the possibilities offered by generative AI, but also concern about falling behind in its use. The real estate sector is one of the sectors expected to see the absolute largest productivity gains per employee if generative AI is effectively implemented, and with the new applications that traditional AI has not addressed, generative AI potentially offers a unique opportunity for the real estate industry to become a leader in technological development. Despite the promising potential of generative AI, research into its opportunities and challenges in the real estate context is still in its infancy, with a limited number of studies exploring the area. The purpose of this study was thus to contribute to the research on generative AI within the context of property management with the goal of providing insights to Swedish property managers about the socio-technical factors that influence the acceptance of generative AI as well as its potential applications within the industry. Through a survey with 172 participants active in property management, driving forces and obstacles linked to the acceptance of generative AI as well as practical areas of use were investigated. The study's findings highlight the factors that lead a user to either accept or reject generative AI. Also highlighted are the tasks in which property managers see generative AI as a complement, can be performed without or with minimal human supervision, and cannot contribute with support within. Results indicate a wide range of tasks that can potentially be supported by generative AI and are thus valuable to property managers with both limited experience with the technology and those with more experience.

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## Sammanfattning

Digitalisering och Artificiell intelligens är för närvarande ett av de mest diskuterade ämnena inom fastighetsbranschen och påstås representera en grundläggande revolution snarare än en kortsiktig trend eller hype. Historiskt sett har fastighetsbranschen varit långsam med att anamma ny teknologi, inklusive traditionell analytisk AI. Sedan OpenAI lanserade ChatGPT i november 2022 har det dock skett ett uppsving i intresset för potentialen hos stora språkmodeller och mer specifikt generative AI. Den nya uppmärksamheten har väckt stor entusiasm över de möjligheter som generativ AI erbjuder, men också en oro över att hamna efter i användningen av den. Fastighetssektorn är en av de sektorerna som förväntas se de absolut största produktivitetsökningarna per anställd om generativ AI implementeras effektivt, och med de nya tillämpningarna som traditionell AI inte har hanterat erbjuder generativ AI potentiellt en unik möjlighet för fastighetsbranschen att bli ledande inom teknisk utveckling. Trots den lovande potentialen hos generativ AI är forskningen om dess möjligheter och utmaningar inom fastighetskontexten fortfarande i begynnelsen, med ett begränsat antal studier som utforskar området. Syftet med denna studie var därmed att bidra till forskningen om generativ AI inom kontexten av fastighetsförvaltning med målet att ge insikter till svenska fastighetsförvaltare om de sociotekniska faktorer som påverkar acceptansen av generativ AI samt dess potentiella tillämningar inom branschen. Genom en enkätundersökning med 172 deltagare verksamma inom fastighetsförvaltning undersöktes drivkrafter och hinder kopplat till acceptans av generativ AI samt praktiska användningsområden. Studiens resultat belyser de faktorer som leder till att en användare antingen accepterar eller avvisar generativ AI. Även belyses de arbetsuppgifter som fastighetsförvaltare ser generativ AI fungera som ett komplement i, kan utföras utan eller med minimal mänsklig övervakning samt inte kan bidra med stöd inom. Resultatet indikerar ett bredd spektrum av arbetsuppgifter som potentiellt kan stödjas av generativ AI och därmed är värdefulla för fastighetsförvaltare med både begränsad erfarenhet av tekniken samt de med mer erfarenhet.

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*Emil Teimert*

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# Chapter 1

# Introduction

*This introductory section aims to introduce the study and explain why it is worth exploring. First, a background to the subject is presented which aims to give the reader a better understanding of why it is relevant to explore further. Then follows a summary of the problem that the study aims to address and investigate. Further, the purpose and research questions are presented. Finally, the limitations of the study are presented as well as an overview of the different parts of the report.*

## 1.1 Background

Research on Artificial Intelligence (AI) dates to the mid-1950s in the US and has experienced periods of success and setbacks since its inception until around 2010 (Hirsch-Kreinsen, 2023). This period was characterized by several AI winters, marked by decreased funding and research in the field. However, since 2010, there has been a continuous development due to advancements in Big Data and more powerful computers. Today, AI has spread and been applied across a wide range of different societal domains (Heanlein & Kaplan, 2019; Hirsch-Kreinsen, 2023). Digitazation and AI are todays most discussed topics in the real estate industry and are more about a fundamental revolution than a trend or hype (Caijas, 2021; Szumilo & Wiegelmann, 2023). With the help of Machine Learning (ML) algortims, AI has previously been recognized for its ability to deal with the abundance of property and transactions data, which is one of the most discussed challenges in the real estate industry (Kabaivanoy & Markovska, 2021). McKinsey & Company (2023) refers to this type of AI as “Analytical AI”, which is more in the goal-oriented direction, where the main use in the majority of different industries has been to produce forceasts and, for example, dynamic models. One of the industries that has not embraced traditional analytical AI to a greater degree is the real estate industry, which has long been known as a slow adapter of new technology. Since OpenAI released ChatGPT in November 2022, the business world has directed a significant portion of its attention towards the opportunities presented by Large Language Models (LLM) and more specifically Generative AI (GAI). This has both sparked excitement about the possibilities, but also raised concerns about falling behind in adoption of the technology (Dencik, Goehring & Marshall, 2023). Goldman Sachs (2023) estimates that integration of GAI could raise global GDP by around 7% and replace approximately 300 million jobs in a ten-year period. In

Sweden, 68% of all jobs are expected to be able to take advantage of GAI, where a successful integration is predicted to increase Sweden's GDP by 9% in a ten-year term. In addition, business services and real estate are predicted to be the next best sector in terms of potential productivity growth per worker, if GAI is implemented and used as a complement (Implement Consulting Group, 2024).

In healthcare, the possibilities with GAI have been described as endless, supporting areas such as drug development, medical interpretations, genetic analysis and more (The Lancet Regional Health-Europe, 2023). Similarly, in the hospitality and tourism industry, GAI have proven to be good at improving staff productivity and increasing customer satisfaction by managing monotonous tasks and helping operations (Dwivedi et al., 2024; Carvalho & Ivanov, 2024). The financial sector is another sector that has been shown to benefit from generative AI, where GAI is used to predict risk management strategies and stock performance, among other things (Chen, Wu & Zhao, 2023; Kim, 2023). In addition, researchers have identified that GAI can streamline accounting processes by automating tasks, interpreting tax regulations and providing guidance to clients (Zhao & Wang, 2024).

GAI brings a new set of uses that traditional AI has not handled, likely representing a new chance for the real estate industry to become an industry at the leading-edge of technology (McKinsey & Company, 2023). Research into GAI 's role in the real estate industry has slowly but surely begun with a few studies examining its opportunities and challenges. For example, Cheung (2023) argues that GAI has what it takes to revolutionize the field of property valuation if professionals within it embrace the technology and become skillful at training their customized models. In addition, Szumilo & Wiegelmann (2024) argues that GAI can improve decision-making, be used in predictive analysis and increase operational efficiency in the real estate industry. Although AI has attracted attention in the real estate sector, it is not yet clear which exact approaches and applications the technology will have the greatest impact on (Viriato, 2019).

In addition to mapping the opportunities and challenges of GAI with respect to applications of the technology, attention has been directed to the more socio-technical aspects of the integration of AI (NIST 2023; OECD 2022). From focusing more on the values that can be realized from a technical perspective, the focus has also shifted towards the user perspective, where above all behavior and acceptance concerning AI has come under the spotlight (Palviainen et al. 2020). Even though the socio-technical aspects have gained more space in the discussion with the implementation of various new concepts and frameworks, they are less researched in relation to the technical, which also applies to the implementation of other technologies (Sovacool & Hess, 2017). There is a great need for more research in the socio-technical aspects of acceptance of new technology (Palviainen et al. 2020), and the frameworks in the area are expected to have a great positive effect by increasing the insights into how they affect applications of AI in different contexts (Sovacool & Hess, 2017). Within the real estate industry, the majority of technical applications have been identified. However, it is required that the

employees of the real estate companies learn to use and train the AI models to realize value creation. Although the socio-technical factors that aim to explain the degree of acceptance of new technology have been investigated in several areas and industries (Venkatesh, Thong and Xu, 2016), and that it has been highlighted that employees in the real estate sector need to accept and learn to use the technology to create value, the research on acceptance of GAI is, to the author's knowledge, very limited within the context of the real estate industry.

## 1.2 Problem

GAI has been proven to bring new opportunities across multiple industries and is predicted to have a huge impact on GDP and the job market, both globally and in Sweden. Despite this, research into the opportunities and challenges of generative AI in the real estate sector is only in its infancy, with very few studies investigating the matter. Furthermore, research on the acceptance of generative AI within the context of the real estate industry is limited, both internationally and nationally, to the author's knowledge.

## 1.3 Purpose and Research Questions

The purpose of this study is to contribute to the research on GAI within the context of property management, with the intention of providing insights to Swedish property managers regarding the socio-technical factors that explain the degree of acceptance of technology such as GAI, as well as potential uses within the industry. To fulfill the purpose of the study, two different research questions have been formulated. The first examines the socio-technical aspects surrounding the acceptance of GAI, and the second the practical aspects surrounding its use. The first research question intends to bring an idea about the factors that lead to a user of GAI either accepting the technology or rejecting it. By exploring the reasons for acceptance or rejection, the question aims to provide guidance to property management companies, employees and managers who wish to implement GAI in their operations, processes and daily tasks. The second research question aims to explore which specific tasks property managers have identified within their daily responsibilities. The answer to the question aims to provide insights to professionals within the industry, and hopefully other industries as well, regarding the types of tasks that GAI can be used in. The insights will be valuable regardless of the degree of use today, where those who have not tried the technology will get an understanding of the types of tasks that are suitable to be performed by or with the support of GAI, hopefully convincing them to take advantage of the technology. Among those already using GAI, the hope is that the study's findings will help them accelerate their use and benefit even more from the technology. To fulfill the purpose of the study, the following two research questions have been asked:

- What are the drivers and barriers for acceptance of generative AI in property management?
- What potential areas of application does generative AI have in property management?

## 1.4 Limitations

The study explores two aspects of GAI in the context of property management where the first is acceptance and the second is areas of use. To answer the first research question regarding acceptance, only one theoretical model, the AI Device Use Acceptance Model, has been selected and considered sufficient to analyze the quantitative data that will be collected through an internet-based questionnaire. The model has previously only been applied in the context of acceptance of more traditional AI in hotel and tourism services. Using a model that has not previously been tested in the same context as this study involves potential risks. One such risk is that comparability between the results of these studies and previous studies may become more difficult. Furthermore, to answer the second research question, only three qualitative open-ended questions have been developed and answered by the respondents through the same questionnaire as the quantitative ones belonging to the first research question. Only one questionnaire has thus been developed, where all respondents have been anonymous, which means that it has been impossible to request clarifications or supplementary questions. Another limitation of this study is that it does not address potential risks that come with the use of GAI, which mainly concerns the findings related to research question two about areas of use. The choice of not focus on the risks is mainly due to three reasons. The first reason is that GAI research in property management is in a very early phase, where the author does not want to limit creative thinking among the respondents but raise the actual practical possibilities. The second reason is since such a consideration would involve an overly extensive study which the author considered not possible to carry out within the limited time frame covered by the study. The last reason is that, like GAI, the regulatory progress linked to the GAI is at an early stage. The absence of risks related to GAI must therefore, when reading this study, be taken into consideration and reflected upon before the reader's own application of any findings in this study is carried out.

# Chapter 2

# Literature Review

*To enhance understanding of what generative AI is and its potential applications within property management, this section of the paper will first provide a thorough overview of artificial intelligence, including machine learning, and how its advanced branch, deep learning, has resulted in generative AI. Following this, relevant research within generative AI and Large Language Models is presented.*

## 2.1 Artificial Intelligence

AI is often defined as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019). It is a broad term including a wide range of computer algorithms capable of performing tasks that traditionally required human intelligence, for example, understanding natural language, recognizing patterns and learning from past experiences (Castelvecchi, 2016). Research on AI dates to the mid-1950s in the USA and has experienced periods of ups and downs since its inception until around 2010. This period has experienced periods of decreased funding and research in the field, so called AI winters. However, since 2010, there has been a continuous development, and today, AI has spread and been applied across various societal domains (Hirsch-Kreinsen, 2023). The resurgence in 2010 can be attributed to the advancements in Big Data and more powerful computers (Haenlein & Kaplan, 2019).

Machine Learning (ML) is a branch of AI that deals with algorithms capable of autonomously solving tasks through data and learning without being explicitly programmed for the specific tasks; the emphasis is on the former, i.e., data and learning (Brynjolfsson & Mitchell, 2017). Depending on the desired outcome, the type of data to be used and analyzed, and the intended results, various types of learning methods exist, such as supervised, unsupervised, semi-supervised and reinforcement learning (Banh & Strobel, 2023).

Supervised learning is often used for classification and prediction and is commonly used in commercial applications. In this method, input data is labeled and known to the user, with the goal of algorithms making as accurate predictions as possible given new and unseen data. Unsupervised learning is often

used when it is not very important to obtain a "correct answer" and involves handling unlabeled data, aiming to identify hidden patterns and groupings. Semi-supervised learning is a combination of supervised and unsupervised approaches. In the last method, reinforcement learning, the focus is on algorithms learning through trial and error, making decisions based on the feedback received (Kühl et al., 2022; Banh & Strobel, 2023). What these and other ML methods have in common is that they possess different discriminative properties, meaning they process data in different ways depending on the purpose and goal (Banh & Strobel, 2023).

ML has been successfully applied in several different contexts in the real estate field and among the 1,200,000 results that appear when searching for "Machine learning AND Real Estate" in Google Scholar's search engine, data gathering and distribution, analytics, automated valuation models, risk assessment and business processes are common areas of use. Baldominos et al (2018), for example, developed a ML software that successfully can identify homes on sales pages that are undervalued compared to the ML-calculated market prices, which in a sales context increases the probability that both sellers and buyers meet on a fair price level. Lorenz et al. (2023) used an extended ML model, which can perform better out-of-sample predicative predictions, to analyze the real estate market and rent levels of different building types change over time, giving investors better insight into which properties are performing best given what phase it is in from an investment perspective. Rafiei & Adeli (2016) developed an ML model that can generate successful economic forecasts regarding the price level of newly built homes as well as homes under construction, by considering a wide range of factors that in themselves consider the time and seasonal aspect.

A more advanced branch within the field of ML is known as Deep Learning (DL). DL, which uses Artificial Neural Networks (ANN or NN), are able to model complex data simulations and automatically notice patterns and correlations in large datasets (Samtani et al., 2023; Goodfellow et al., 2016). In DL, NN are models designed to mimic the human brain and can be viewed as building blocks composed of many "hidden" layers in a mature structure. This structure, in turn, helps algorithms in learning different levels of information from the dataset, enhancing their ability to perform specified tasks. By utilizing this technology, DL can handle all types of data (LeCun, Bengio & Hinton, 2015).

## 2.2 Generative AI

Through the development of DL, a subcategory of models known as Deep Generative Models (DGM) has been introduced, opening a lot of new applications and possibilities, including the generation of new content based on existing data (Lehmann & Buschek, 2020). DGMs are built on NN with multiple hidden layers that, when trained correctly, can generate a large number of outputs such as images, voices, or videos using complex probability distributions. Within DGM models, various training methods exist such as Generative Adversarial Networks, Variational Autoencoders and Transformers (Ruthotto & Haber, 2021; Banh & Strobel, 2023). The latter has become the foundation for a range of leading-edge

tasks in natural language processing. With the help of so-called self-attention mechanisms, Transformers can identify long-range dependencies in the data they are fed, making them suitable for a many different types of tasks (Banh & Strobel, 2023). The Transformer architecture has become the basis for later developments such as Generative Pre-trained Transformers (GPT). GPT, with its ability to be trained with extremely large amounts of unlabeled data and training parameters, is capable of handling various tasks in text, image, video, and audio processing (Banh & Strobel, 2023).

GAI is the result of advancements in DL, making it possible to generate unique, realistic and creative content, in contrast to more traditional AI tasks (Banh and Strobel, 2023). It is a subcategory of DL that uses ANN and, through supervised, unsupervised and semi-supervised learning, can handle both labeled and unlabeled data to generate a wide range of outputs (Ghimire, Kim & Acharya, 2024). The purpose of GAI is to generate new content such as text, audio, images, code and simulations. The relevance of the content the model generates is directly linked to the quality and quantity of training data (Budhwar et al., 2023).

There are four main types of generative AI: text-to-text, text-to-image, text-to-video and text-to-task (Ghimire, Kim & Acharya, 2024). Text-to-text models are trained to find relations in text pairs, meaning that through the context and connection of words in a sentence or larger text serving as input prompts, they generate an output in text format (Li, Su & Liu, 2018). Text-to-image models are trained to transform text descriptions into image representations using techniques such as generative adversarial networks or transformer architecture (Zhang et al., 2023). Text-to-video models are trained to generate video representations through text descriptions, enable to handle both short sentences and long scripts (Liu et al., 2023). The last type of GAI, text-to-task models, is trained to perform various tasks based on text input, with examples of tasks including searches and predictions (Lei, Barzilay & Jaakkola, 2016).

## 2.3 Large Language Models

In the article by The Lancet Regional Health-Europe (2023), the potential of GAI in healthcare is described as almost limitless with applications such as drug development, medical interpretation, genetics and laboratory results and much more. Despite its young nature and limitations, GAI is seen to be a tool that can have a transformative effect in the field when it is further developed alongside strict regulation and careful use.

Dwivedi et al. (2024) examine existing applications as well as challenges with GAI in various areas of the hotel and tourism sector and suggest that the technology will have a very positive transformative effect on the industry. Above all, tools such as ChatGPT are able to supplement staff productivity and especially help ease the burden when it comes to monotonous tasks, which the researchers believe will in the long run have a positive effect on efficiency and employee well-being. Dwivedi et al. (2024) emphasize the need to ensure that employees learn to use the tools in order to get the most out of them.

Another study by Carvalho & Ivanov (2024) verified the findings of Dwivedi et al. (2024) and highlight that Chatbots based on ChatGPT can have a great positive effect on the efficiency of front-of-house work and improve customer satisfaction in all stages of a hotel and tourism experience. Furthermore, Carvalho & Ivanov (2024) argues that back-of-house work can potentially get a big boost and strengthen staff efficiency by, for example, being used for tasks that require writing, analysis of reviews and other various creative processes. The researchers highlight that more research is needed into the possibilities and implications of the technology to mitigate its risks, which are still considered unclear given the early stage of generative AI in the field.

Chen, Wu & Zhao (2023) examines, among other things, the progress of GAI in business and finance and what practical application GAI-tools can have to revolutionize data analysis in both the field and academia. Through empirical tests, the researchers argue that tools such as ChatGPT can be used to predict both companies' ability to manage risks and the return performance of stocks. Chen, Wu & Zhao (2023) concludes that GAI is associated with both opportunities and challenges in the field of business and finance, with examples of the former taking the form of better access, cost savings and better efficiency. According to the researchers, examples of challenges are the lack of regulations, data security and uncertainty in, for example, chatbots' output. Other studies that argue that GAI can be used in Finance are Kim (2023) who, through an integration of ChatGPT in a quantitative investment method, argues that generative AI can improve portfolio efficiency by leveraging its macroeconomic and financial understanding. Pelster & Val (2024) concluded through a life experiment that ChatGPT can successfully identify stocks that deliver superior performance the following month through its ability to identify, analyze and evaluate company news. Fatouros et al. (2023) show in their study on the potential of GAI and ChatGPT in financial sentiment analysis that tools such as the latter, with carefully designed prompts, can perform approximately 35% better than previously established models in terms of sentiment classification and show a 36 % higher correlation with market returns – which implies that ChatGPT can have a huge transformative effect in the field.

Within the construction industry, there is a significant research gap regarding GAI and its potential applications in the field. This gap is likely due to the fact that GAI is in a very early stage and the general slowness of the construction industry in adopting new technologies. There is a strong need for research in this area, as the industry already faces challenges that could potentially be addressed by the opportunities offered by GAI (Ghimire, Kim & Acharya, 2024). Zheng and Fischer (2023) introduce an application of GAI in Building Information Modeling (BIM), where they successfully developed a virtual assistant, "BIMS-GPT" using GPT technology. This virtual assistant supports searches in BIM models using natural language. With a text prompt as input, the assistant understands the user's intentions with the BIM program. It can extract relevant information from the BIM database, generate a textual response and deliver the requested 3D visualization. In a case study demonstrating the assistant's functionality on a hospital building, it achieved an accuracy level of 99.5% in understanding user text

input and generating the desired output. The GPT application represents progress in the continued integration of GAI in the construction sector, increasing access to BIM for more professionals in the industry Zheng and Fischer (2023).

In another study by Prieto, Mengiste & García de Soto (2023), the potential of ChatGPT was explored in the context of project scheduling, focusing on more repetitive and time-consuming tasks. After language models generated a construction plan for a simple building project, participants concluded that ChatGPT is capable of producing consistent construction plans with a logical work strategy that meets the specified requirements. Although participants agreed that the technology has limitations and needs further development, they were positive about using the technology in future work. In the study by Moon, Chi & Im (2022), a pretrained BERT (Bidirectional Encoder Representations from Transformers) model in Natural Language Processing (NLP) was employed to detect risks in construction contract clauses. The researchers identified clauses that are often subject to disagreements and disputes and then developed a clause classification model based on BERT. The model proved to be highly effective for its intended purpose, and several possibilities were identified, such as the ability to identify the most likely risks based on context and key stakeholders involved.

In the study by Chung et al. (2023), the researchers investigated how ChatGPT and BARD (Building Architecture Reporting Data) could be used in various ways within the construction industry. One potential application they identified was in automating construction drawing and document management, particularly because much of the information in current construction projects is initially drawn and written on paper and then scanned. You et al. (2023) explored in their study whether GAI, specifically ChatGPT-4, could bring new possibilities to robot-based assembly in the construction industry, an area traditionally relying on more traditional AI methods. The team developed a robot called RoboGPT, used in two case studies and 80 tests involving various real-world construction tasks. With the assistance of ChatGPT, the robot demonstrated the ability to handle more complex and dynamic tasks and adapt well to on-site changes compared to previous methods. However, the researchers noted that further research is needed to determine if ChatGPT and its application in the field should become a standard practice. Lastly, Cheung (2023) investigated how GAI, specifically ChatGPT, can be used in property valuation in accordance with RICS – Golden Standard, which emphasizes the importance of "consistency, objectivity, and transparency" in valuations to make them credible. The focus of the study was on how to maximize the benefits of ChatGPT using a technique called Chain of Thought-prompt engineering. This involves developing smart prompts as input to guide the model in generating outputs aligned with the RICS – Golden Standard.

# Chapter 3

# Theoretical Framework

*This chapter introduces the theoretical model used to answer research question one. First, the model is presented, followed by a review of its key factors. Then, earlier applications are presented followed by strengths and weaknesses with the model, which aims to give the reader an understanding of the possibilities and disadvantages of using it in the context of this study.*

## 3.1 AI Device Use Acceptance Model

The AI Device Use Acceptance Model (AIDUA) is a theoretical model developed by Gursoy et al. (2019) which aims to explore the acceptance of AI. The model is based on Lazarus & Fowler's (1991) cognition-motivation-emotion framework and was developed in connection with the progress of AI. Gursoy et al. (2019) argues that previous theoretical models that explore acceptance of technology do not have as good predicative ability on AI acceptance, which is also in line with Sohn & Kwon (2020). Unlike other well-known technology acceptance models such as the Technology Acceptance Model (TAM) by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), Gursoy et al. (2019) argues that the AIDUA model has been designed to measure intelligent technology such as AI as opposed to non-intelligent for which the previous two were found to be suitable. The AIDUA model by (Gursoy et al., 2019) is based on previous technology acceptance models and examines the acceptance of AI through three stages, which all consist of determinants presented in Illustration 1.

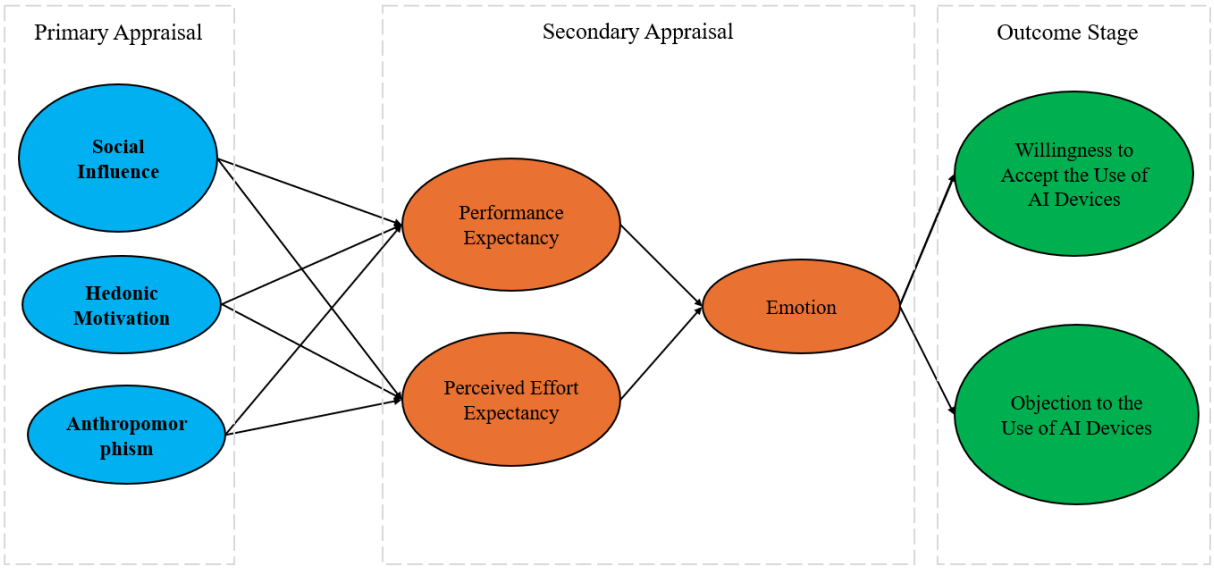


**Illustration 1**. AIDUA model by Gursoy et al. (2019); colors added by the Author

# 3.2 Key Factors

The model proposed by Gursoy et al. (2019) consists of three stages that together make up the acceptance generation process and which they argue every customer goes through when faced with the use of an AI Device: Primary Appraisal, Secondary Appraisal, and the Outcome Stage. The three stages have contained two to three determinants each. In the Primary Appraisal these are Social Influence, Hedonic Motivation and Anthropomorphism. In the Secondary Appraisal it is Performance Expectancy, Perceived Effort Expectancy and Emotion. The last, Outcome Stage, contains Willingness to Accept the Use of AI Devices and Objection to the Use of AI Devices. Gursoy et al. (2019) tested the model through a survey study with a sample size of 439 surveys and then conducted a data analysis using a CB-SEM method of the results.

## Primary appraisal

The first factor in the Primary appraisal is Social Influence, which aims to examine how one's social circle's use and think of AI affects a potential user of it (Gursoy et al., 2019). The research on how social norms influence a person's decisions is extensive. Social Identity Theory by Tajfel and Turner (1979), suggests that following the norms within a group will lead to a sense of belonging, which for most of is something positive. This further suggests, within the context of AI, that if one's social circles have a positive view of AI, it will reasonably lead to one having it as well. Gursoy et al. (2019) found that Social Influence is positively correlated with Performance Expectancy and thus that potential users' behavioral intentions are reflected in how their social circles and groups view the matter, whether they accept it or not. The researchers believe that this influence can be so strong that before a potential user

creates an image of the pros and cons of AI technology, a so-called "priming effect", will be created in the user, which either revolves around how they think other people see on the use, pros and cons, or how they think it will affect their social identity. These external motivational factors based on social influence then determine whether they form a positive or negative Performance Expectancy. Gursoy et al. (2019) also found that Social Influence does not have a relation to Effort Expectancy, which they argue may be due to a strong social influence, i.e. they do not worry about effort if the group thinks the technology is good.

The second factor in the Primary Appraisal is Hedonic Motivation, which aims to measure the degree of pleasure a user feels when using AI or is expected to feel if they have not already tried it (Gursoy et al., 2019). This factor has previously been described as one of the absolute most important factors when it comes to technology acceptance (Venkatesh, Thong & Xu, 2012). Gursoy et al. (2019) found that Hedonic motivation was strongly positively correlated with Performance Expectancy and negatively correlated with Perceived Effort Expectancy. Gursoy et al. (2019) argues that potential users' view of AI technology, i.e. whether they consider it to bring pleasure and stimulation or not, will have a large impact on their behavioral intentions. If they think the technology is good, possibly because of previous experience with other technology, the fact of how much effort is required will be less decisive, and the opposite if the user thinks the technology is boring and has no previous experience.

The last factor in the Primary Appraisal is Anthropomorphism, which aims to measure the feeling that something that is not human is perceived to be, e.g. a robot with a human-like appearance or that can communicate through speech (Kim and McGill, 2018). Gursoy et al. (2019) also found that the degree of anthropomorphism has an impact on potential users' perceived effort expectancy, which they believe may be due to users being faced with two activities instead of one (in the case where the degree of anthropomorphism would be zero), partly to interact with a human (robot with human tendencies) and learning a new advanced technology.

## Secondary appraisal

The first two factors in Secondary Appraisal are Performance Expectancy and Perceived Effort Expectancy, which aim to explain the degree of positive or negative attitude a potential user has towards AI (Gursoy et al., 2019). Performance Expectancy aims to explain the degree of perceived benefit the AI tool has, i.e. how well it performs. In contrast, Perceived Effort Expectancy aims to measure the degree of how difficult it is perceived to be in terms of usage, alternatively how time-consuming it is. These two factors will then lead to an emotion that can be further analyzed to gain an understanding of whether the AI tool is accepted or not. The results of Gursoy et al. (2019) indicated a strong positive relation between Performance Expectancy and Emotion, and a weak negative relation between Perceived Effort Expectancy. Their findings thus indicate that if a user believes that the AI tool works

well, they will experience good feelings. However, if they experience that using it is difficult or that it requires a great sacrifice in the form of time spent, they will experience slightly negative feelings.

### Outcome Stage

The last stage in the acceptance process is the Outcome Stage, which contains the factors Willingness to Accept the Use of AI and Objection to the Use of AI. Gursoy et al., (2019) argues that the degree of these two will be affected by the user's perceived emotions connected to the use of AI, which itself is based on how the factors in the two previous appraisals have performed. Willingness to Accept the Use of AI measures the degree of willingness to use AI tools in the future and is suggested to be positive if a potential user's perceived feelings are positive. In contrast, Objection to the Use of AI measures the degree of reluctance to use AI tools in the future and is suggested to be negative if the potential user has bad feelings. Gursoy et al. (2019) found a strong positive relationship between Emotion and Willingness to Accept the Use of AI and a somewhat weaker negative relationship between Emotion and Objection to the Use of AI.

## 3.3 AIDUA Framework Applications

In the study by Kelly, Kaye & Oviedo-Trespalacios (2023), a systematic review of user acceptance and AI technology is carried out, where several acceptance models are presented and compared. Of the sixty articles that they report and that used one of the presented theories, four of them used the AIDUA model in their research. Of these four articles, the theory was used in three of the cases within the context of customer service and the fourth in tourism (Kelly, Kaye & Oviedo-Trespalacios, 2023).

In the study by Lin, Chi & Gursoy (2020), the AIDUA framework was used to investigate hotel guests' acceptance of using AI-controlled robot devices in hotel service contexts, both in full-service hotels and in more limited-service hotels. Unlike the traditional AIDUA model, Lin, Chi & Gursoy (2020) also tested how hedonic motivation affects positive emotions in hotel guests, a relationship that Gursoy et al. (2019) did not explore in the development of the original AIDUA model. Lin and colleagues tested the influence of all determinants on performance expectancy and perceived effort expected through a survey study of 605 samples. After statistical analysis through the CB-SEM method, Lin, Chi & Gursoy (2020) determined that their modified AIDUA model could effectively explain hotel guests' acceptance of AI, and in relation to the non-modified AIDUA model, it proved to have a significantly better ability to explain AI acceptance within the hotel context. In comparison with the model of Gursoy et al. (2019) found Lin, Chi & Gursoy (2020) that their modified AIDUA model that the determinant social influence had a significantly greater influence on performance expectancy; that hedonic motivation had a greater influence on performance expectancy and negatively on effort expectancy; that anthropomorphism had a greater influence on effort expectancy; that performance expectancy had a greater influence on positive emotions and that positive emotions had a greater influence on willingness of use.

In the study by Roy et al. (2020), the researchers validate both the original AIDUA model by Gursoy et al. (2019), as well as the modified AIDUA model as Lin, Chi & Gursoy (2019) presented in their study, though within the Indian luxury hotel sector. Roy et al. (2020) used, just like the previous two, a survey study, where they collected answers from 210 respondents by having hotel guests answer it on site. In addition to questions linked to demographic information, the survey contained 32 questions that were answered on a scale of 1-5 (strongly disagree - strongly agree), where six questions were linked to the determinant social influence, four to hedonic motivation, four to anthropomorphism, four to performance expectancy, three to effort expectancy, five to emotion, three to willingness to use AI device and three to objection to use AI devices (Roy et al., 2020). After the collected data was analyzed through SEM-AMOS, CFA, CB-SEM and CFA methods, Roy et al. (2020) state that their empirical results validated the AIDUA framework within the hospitality sector.

## 3.4 Strengths and Drawbacks

AI can be used and create value for many people if they use it in a good way, but before this is possible, they need to accept the technology, if the level of acceptance is low it risks having a negative impact on technological innovation and misuse of useful resources (Kirlidog & Kanyak, 2013). Measuring the acceptance of AI through theoretical models allows a better understanding of the variables that have the greatest impact on people's acceptance of the technology and of the theories previously used for this purpose, AIDUA is the most recently developed (Kelly, Kaye & Oviedo-Trespalacios, 2023). Despite its young age and limited use in research, the research where AIDUA has been applied indicates that it delivers promising results (Kelly, Kaye & Oviedo-Trespalacios, 2023). One of the advantages that comes with the theory, and makes it stand out from the crowd of similar theories, is that it first considers two different outcomes (willingness to use and objection), and that it focuses on intelligent technology such as AI. This allows a more comprehensive and detailed analysis which increases its predictive ability (Kelly, Kaye & Oviedo-Trespalacios, 2023). The main drawback with AIDUA is the fact that it is not as explored as previous technology acceptance models such as TAM and UTAUT (Kelly, Kaye & Oviedo-Trespalacios, 2023).

# Chapter 4

# Method

*This section aims to provide a thorough understanding of the method used in this study. The section begins with an introduction to the research design. Then follows a description of data collection, where respondent selection and the data collection are presented. Next, the approach to the data analysis is presented, where, among other things, the quantitative and the qualitative analysis methods are presented, followed by a discussion about the quality of the analysis and ethics.*

## 4.1 Research Design

This cross-sectional study will use a concurrent embedded research design with an abductive approach, where an exploratory qualitative and an explanatory quantitative method will be used at one single data collection occasion in the form of an internet-based questionnaire. In the survey, 24 of the total 27 questions will be of the explanatory quantitative type with cross-questions and only three questions will be of an exploratory qualitative nature and require open answers that the respondents can answer in own text. The fact that an abductive approach has been chosen is because the study intends to explore something that within the context of the chosen industry is something new (Saunders, Lewis & Thornhill, 2016).

The study aims to answer two research questions, where the first, "What are the drivers and barriers for acceptance of generative AI in property management?", will be answered through the quantitative explanatory method. This method is suitable as it enables the identification of causal relationships between the responses and makes it possible to analyze these through the selected model (Saunders, Lewis & Thornhill, 2016). The second research question, "What potential areas of application does generative AI have in property management?" will be answered through the exploratory qualitative method. This method is particularly suitable because it enables answers that directly reflect the respondents' own experiences and insights, which would otherwise not have been noticed to the same extent when using, for example, cross-questions (Saunders, Lewis & Thornhill, 2016).

Advantages of an embedded quantitative and qualitative method include its less time-consuming nature compared to other mixed methods, as well as its ability to often produce richer data than a mono-method where only one research method is used (Saunders, Lewis & Thornhill, 2016). Other advantages of using a mixed method such as concurrent embedded research design is that the quantitative and qualitative answers in the survey will complement each other and lead to a better overall understanding and the results can be verified more effectively (Saunders, Lewis & Thornhill, 2016).

## 4.2 Data Collection

In order to ensure a successful survey study, great considerations were made regarding which data would be collected, how the questions would be formulated and which people would answer the survey.

### 4.2.1 Respondent Selection

For this study, 598 questionnaires were sent out, of which 172 responded. The study used a sampling strategy based on non-probability purposive homogeneous sampling. The strategy was chosen to explore a specific group, in this case property managers employed at Swedish property management companies. Saunders, Lewis & Thornhill (2016) argue that this type of sampling is suitable because it enables responses from people in the same profession faced with similar tasks, which allows the sample to be explored on a deeper level. Another advantage of a homogeneous sample group is according to Saunders, Lewis & Thornhill (2016) that it does not require a large sample size.

The respondents were selected based on two main factors. The first being that they work in property management to ensure that their experience and knowledge was relevant for the purpose of the study. The second availability of their contact details, which were either publicly available on the property management company's website or on the housing association's website.

The people who were selected were contacted via email, where a description of the survey and its purpose was described carefully but briefly. The first round of mailings was spread over four business days and sent out between 7:50 am to 8:10 am to increase the likelihood that they noticed the email during the day. The week after the first mailings, reminder mailings were sent to those who did not return, stating that they either completed or did not intend to complete the survey, this to increase the likelihood that more people will respond but also reduce the risk that people who are willing to answer the survey did not notice the first mailing due to various reasons.

The first mailings were made, without the author’s knowledge, during the schools' Easter holiday, which in some families means that the parents take time off from work to spend time with their children. This was verified when about 30 people's emails gave auto-replies that they were on Easter vacation. For this reason, as well as the fact that email baskets fill up when others send emails and previous emails end up at the bottom and are at risk of being missed, a reminder mailing was considered particularly appropriate.

In addition to the 598 people who were contacted via email, a post was also published on a large property management forum in Sweden. The post consisted of an introduction to the study and welcomed all people in the industry to participate. It contained a link and QR code to the same survey that the 598 people received, with the exception that their answers ended up in a different collection with the aim of being able to separate the two. After the post had been online for approximately two weeks, around 10 people had responded to the survey. Since the number of responses from the first collection method was substantially greater, it was considered reasonable to only continue with those, and thus exclude the responses collected through property manager forum.

### 4.2.2 Collected data

In this study, a survey strategy in the form of an internet questionnaire was used to collect primary data. A quantitative explanatory method was used together with a qualitative explorative. In the context of a study using a questionnaire as a collection method, quantitative explanatory methods are known to work better than more qualitative explorative, primarily due to the normally standardized nature of the questions (Saunders, Lewis & Thornhill, 2016). Qualitative exploratory questions were chosen to be included in the survey study because it allows a greater exposure of respondents, which in this study was considered more relevant than fewer and more detailed answers from a small percentage of people that would have been the case in, for example, interviews. Furthermore, the three qualitative questions (Q25-Q27) were considered sufficient to answer research question two as they allow open answers and are designed in such a way that by answering them, they directly answer the question.

**Collection of quantitative data**

The study's first research question, "What are the drivers and barriers for acceptance of GAI in property management?", was determined to be best answered through a quantitative approach with explanatory questions. As the respondents' answers would be analyzed through the AIDUA Model by Gursoy et al. (2019), questions were formulated in alignment with the questions that Gursoy et al. (2019) used in developing the framework. As thoroughly described in Chapter three, the AIDUA is a conceptual framework with three stages that together make up the AI Acceptance process. Six categories of questions were developed based on the six determinants within the first two steps of the acceptance process: primary appraisal, and secondary appraisal. In the questionnaire, three questions were produced per category, were most were based on the questions Gursoy et al. (2019) developed with the only difference that the questions in this survey were designed to fit the context of GAI use in property management, in contrast to customers in the hospitality sector. The questions were given in Swedish as the property managers worked in Swedish property management companies. All questions are displayed below with an English translation together with the sources of the original questions, please see appendix for original questions in Swedish.

**Table 1.** Survey questions related to RQ1

| | | |
|---|---|---|
| **Primary Appraisal** | | |
| **Social Influence** | | **Reference** |
| Question 1 | If my colleagues increased their use of generative AI, so would I. | Lu, Cai & Gursoy, 2019 |
| Question 2 | I would increase my use of generative AI if my boss encouraged me to. | Gursoy et al., 2019 |
| Question 3 | Using generative AI is seen as prestigious in my social circles. | Gursoy et al., 2019 |
| **Hedonic Motivation** | | |
| Question 4 | Using generative AI is entertaining. | Gursoy et al., 2019 |
| Question 5 | Using generative AI is satisfying when it clearly contributes positive effects in my work. | Lu, Cai & Gursoy, 2019 |
| Question 6 | I would use generative AI even if it did not contribute clearly positive effects in my work. | n/a |
| **Anthropomorphism** | | |
| Question 7 | I feel that generative AI has its own opinions. | Gursoy et al., 2019 |
| Question 8 | I feel that generative AI has feelings. | Gursoy et al., 2019 |
| Question 9 | In the future, generative AI will have a consciousness of its own. | Lu, Cai & Gursoy, 2019 |
| **Secondary Appraisal** | | |
| **Performance Expectancy** | | **Reference** |
| Question 10 | Generative AI provides more consistent answers than humans. | Lu, Cai & Gursoy, 2019 |
| Question 11 | Generative AI generates more accurate information (fewer errors) than what humans generate. | Lu, Cai & Gursoy, 2019 |
| Question 12 | Generative AI provides more reliable services than humans do. | Gursoy et al., 2019 |
| **Effort Expectancy** | | |
| Question 13 | Learning how to use generative AI takes too long. | Gursoy et al., 2019 |
| Question 14 | It is too time consuming to use generative AI. | Gursoy et al., 2019 |
| Question 15 | It is difficult to understand how to use generative AI in daily tasks. | Gursoy et al., 2019 |
| **Emotion** | | |
| Question 16 | Using generative AI makes me feel stressed/relaxed. | Gursoy et al., 2019 |
| Question 17 | When I use generative AI, I feel dissatisfied/satisfied. | Gursoy et al., 2019 |
| Question 18 | Generative AI makes me feel desperate/hopeful | Gursoy et al., 2019 |
| **Outcome Stage** | | |
| **Willingness to Accept** | | **Reference** |
| Question 19 | I am willing to learn how to use generative AI in my work | Gursoy et al., 2019 |
| Question 20 | I would like to use generative AI in my work more than I do today | n/a |
| Question 21 | It is likely that I will start using generative AI in my work | Gursoy et al., 2019 |
| **Objection to Use** | | |
| Question 22 | I prefer to use other sources of information over generative AI | n/a |
| Question 23 | Generative AI processes the information in a less humanized way | Gursoy et al., 2019 |

| | | |
|---|---|---|
| Question 24 | I prefer human contact in service transactions | Gursoy et al., 2019 |

**Collection of qualitative data**

The study's second research question, "What potential areas of application does generative AI have in property management?", was determined to be best answered through a qualitative approach with exploratory open questions. The questions were formulated in such a way that they would bring as much insight into the use as possible, see questions 25-27 below.

**Table 2**. Survey questions related to RQ2

| **Application of Generative AI** | |
|---|---|
| Question 25 | Which of your daily tasks can generative AI work as a support in? |
| Question 26 | Which of your work tasks can be performed in their entirety, or almost, with the help of generative AI? |
| Question 27 | Which of your daily tasks absolutely cannot be solved with generative AI? |

**Collection of background data**

The respondents were asked at the beginning of the questionnaire to state gender, age, industry, work role/position, main area of responsibility and number of years in the industry. Respondents were also asked to indicate their current degree of GAI experience use by choosing one of six statements that best fit them, see Table 3. The background questions were intended to provide a better understanding of the variation that may exist among respondents and thereby increase the likelihood of being able to interpret the results in a more nuanced way.

**Table 3**. Survey questions related to background information

| **Question** | **Which of the following describes your use of generative AI (eg ChatGPT and Bing Copilot) best?** |
|---|---|
| Alt. 1 | I haven't heard of it |
| Alt. 2 | I've heard of it but haven't used it |
| Alt. 3 | I have tried but not continued to use it |
| Alt. 4 | I use it once a month |
| Alt. 5 | I use it once a week |
| Alt. 6 | I use it every day |

# 4.3 Data Analysis

To optimize adaptation, this study will present the results together with the analysis (Blomkvist and Hallin, 2015). Data collected to answer the respective research question will be presented and analyzed separately. Data pertaining to research question one, which deals with quantitative data, will be

presented and analyzed by first breaking down and analyzing the respondents' stance on the various questions they answered, and then, both in fluent text and statistically, analyzing the collected data through the theory AIDUA model by Gursoy et al. (2019). Data related to research question two, which deals with qualitative data, will be categorized and presented and then analyzed by comparison with how other industries use generative AI.

## 4.3.1 Quantitative Analysis

The result of collected quantitative data will initially be presented in flowing text that analyzes the relationships between the key components of the AIDUA model. By proceeding in this way, a narrative analysis method is enabled where the various findings found within each key factor are allowed to be analyzed and provide insights in the same sequence as they are presented in the model, which is a good approach when you have many data sources and a lot of data to analyze (Blomkvist and Hallin 2015). Furthermore, the collected data will be analyzed statistically in line with Gursoy et al. (2019). To facilitate the work, the statistical calculation will be divided into two models, where the first, called the measurement model, will undergo a CFA analysis through the tools SPSS, SPSS AMOS and Excel to examine how well the model fits. Furthermore, a maximum likelihood estimation-based CB-SEM will be carried out through the SPSS AMOS tool to examine the structural model and the relationships between key factors in the AIDUA model.

## 4.3.2 Qualitative Analysis

The results obtained from the survey study and which are of a qualitative nature will first be generalized to a certain extent to avoid an abundance of similarly identified tasks. Furthermore, the generalized tasks will be categorized and placed within appropriate areas to facilitate interpretations of the findings. Since the qualitative data collected stems from three different questions that aim to investigate GAI's potential areas of use, the findings from each question will be presented and analyzed separately.

## 4.3.3 Quality of Research

In order to maintain a high research quality, the study's generalizability, validity and reliability have been taken into account. By considering these three common quality measures, it increases the likelihood that the study's results are both reliable and valid, but also potentially generalizable to other industries.

### 4.3.3.1 Generalizability

Generalizability is a common measure used to determine the quality of a research paper and refers to how well the results from a study can be generalized to a larger population or to other situations outside of the specific study (Saunders, Lewis & Thornhill, 2016). Since this study has used an internet-based survey study as a data collection method, there are several risks regarding its generalizability. An example of a threat to generalizability is the selection method, which in this study was non-probability

purposive homogeneous sampling. This choice of selection method therefore means that the respondents come from the same industry and have similar tasks, in this case within property management. This will therefore have an impact on the generalizability of the study because it focuses on understanding specific phenomena within a limited context. Another aspect of the questionnaire, which favors generalizability, is that the questions have not been formulated in a way that excludes the possibility that the answers may also apply to other industries.

#### 4.3.3.2 Validity

The collection of primary data in this study took place at one single collection occasion in the form of an internet-based questionnaire, a collection method where great emphasis is placed on internal validity (Saunders, Lewis & Thornhill, 2016). Internal validity within the context of a questionnaire is about how well the questionnaire measures what it intends to measure, in this study's case the acceptance rate of GAI measured through the eight constructs constituting the AIDUA model by Gursoy et al. (2019) as well as potential uses of GAI. A common approach when estimating questionnaire validity is to divide it into three parts, content validity, criterion-related validity and construct validity (Saunders, Lewis & Thornhill, 2016). The first of the three, content validity, aims at coverage and how relevant the questions in the questionnaire are. The questionnaire developed in this study can be considered to have questionable content validity to a certain extent, above all regarding the collection of quantitative data in terms of its coverage. The reason for this lies in the fact that only three questions were asked for each construct in the AIDUA model, which is fewer than several previous studies that used the same theoretical framework. Regarding the relevance of the questions, almost all were formulated in line with questions that similar studies (Gursoy et al., 2019; Lu, Cai & Gursoy, 2019) used, which is a good way to ensure content validation (Saunders, Lewis & Thornhill, 2016). The second type of validity, criterion-related validity, aims to assess how well a result correlates with or predicts a specific future outcome or behavior (Saunders, Lewis & Thornhill, 2016). As this study aims to investigate the acceptance and practical uses of GAI in property management, which is so far unexplored to the author's knowledge, the criterion-related validity of the study can be seen as questionable. More specifically, the behaviors and usage data identified in this study cannot be verified to a sufficient extent because there is no previous research to compare with in the context of property management. By relating the findings to findings from other industries, certain criterion-based validity can be strengthened. The last type of validity, construct validity, can be divided into convergent validity and discriminant validity (Saunders, Lewis & Thornhill, 2016). The former examines the extent to which different measurements that theoretically should be related to each other are, and the latter the extent to which measurements that theoretically should be different, are different (Saunders, Lewis & Thornhill, 2016). In this study, quantitative data collected regarding these two indicators were tested for construct validity through a CFA, where divergent validity is presented in Table 13 and discriminant validity in Table 14. Through

comparison with suggested cut-of values and previous research, the study's construct validity could be assessed somewhat questionable.

#### 4.3.3.3 Reliability

Reliability is another common measure used in evaluating the quality of research, which aims to explain its consistency (Saunders, Lewis & Thornhill, 2016). The measure gives an indication of how repeatable the research methodology is, where high reliability means that the results will probably be similar in another study where they use the same method (Saunders, Lewis & Thornhill, 2016). This study has used an internet-based questionnaire as a collection method, which comes with several possible risks regarding reliability. A threat to the study's reliability is the fact that many of the respondents do not have any major practical experience with GAI, which means that their answers to some of the questions can be considered unreliable, this applies above all to the open-ended questions that investigate work tasks where GAI may or may not be used within. To mitigate the threat, the author collected responses from a relatively large population within the same industry and made it clear that these were suggestions and not necessarily tested and verified. The high number of respondents who took part in the survey study, as well as the development of most of the questions in line with previous research, also meant a milder threat to misunderstandings of the questions. A threat that was identified in connection with the analysis of collected quantitative data, where relationships between different constructs in the AIDUA model would be calculated statistically, was its internal consistency. Internal consistency is a measure of how well different parts of a measurement instrument measure the same concept or characteristic (Saunders, Lewis & Thornhill, 2016), which in this study was measured by examining the various constructs' Cronbach's Alphas as part of the conducted CFA. All Cronbach's Alphas were above the suggested cut-off limit of 0.7 except for Objection to the Use of AI, which indicates an overall good reliability.

### 4.3.4 Ethics

To ensure high research ethics, the author has acted respectfully and honestly towards all participants in the development of the study. To ensure this, the author has considered and followed the study-relevant principles of Saunders, Lewis & Thornhill (2016). The first principle that the author has considered is "integrity and objectivity of the researcher", which has been adhered to by the author acting openly, truthfully and promoting accuracy throughout the work. The principle "Privacy of those taking part" has also been considered. Among other things, the author has consistently treated the respondents in a respectful manner and on all occasions avoided harm to participants in all its forms. All data collected by the respondents has been anonymous and designed in such a way that does not arouse embarrassment, stress, discomfort or any other bad feelings. All respondents knew that it was voluntary to participate in the survey study and that it is thus completely up to them to participate or not, without any subsequent consequences. Before possible participation, the respondents have received all relevant information

about participation before they had to choose either to proceed to the questions or to refrain. It has also been voluntary to answer the questionnaire's questions, where there was an opportunity to refrain from the questions if the respondent wanted to. When analyzing the data, all respondents' answers have been anonymous, and all reported findings are accurate regardless of any contradicting expected outcomes.

# Chapter 5

# Results and Analysis

*This chapter intends to present the study's results and analysis thereof. First, the demographic profile of the respondents who carried out the survey study, on which the results are based, is presented. After that, the findings from the quantitative part of the survey study, which aims to answer the study's first research question, are presented and analyzed. Finally, the findings from the quantitative data collected in the survey study and the analysis of this are presented.*

## 5.1 Demographic profile of respondents

The distribution of male and female respondents was very even, with 47.6% male respondents and 52.4% female respondents (Table 4). Among the respondents, the most majority age was between 36 and 45 years (33.5%), followed by an age between 46-55 (26.2%) and 26-35 (22.6%). Almost all respondents were active in the property industry (98.8%) and within this a majority were property managers (76.9%). Among other respondents, financials were linked to property management most often (13.1%), followed by project management (3.7%) and technical property management (2.5%). Most respondents have worked in the property industry for 3-10 years (35.4%) and a slightly smaller proportion for 10-20 years (32.3%). 3.2% of the respondents use GAI daily, 7.6% once a week and 21.7 once a month. Of the 93.6% of the respondents who had heard about GAI, 22.3% of them had tried it but did not continue to use it, and 38.8% of them had not tried it despite being familiar with it.

**Table 4.**
Demographic profile of respondents

| Items | Category | Distribution (%) |
|---|---|---|
| Gender | Male | 47.6 |
| | Female | 52.4 |
| Age | 18-25 | 1.8 |
| | 26-35 | 22.6 |
| | 36-45 | 33.5 |
| | 46-55 | 26.2 |
| | 55+ | 15.9 |
| Industry | Real Estate | 98.8 |
| | Other | 1.2 |
| Occupation | Property management | 76.9 |
| | Financials | 13.1 |
| | Project management | 3.7 |
| | Technical property management | 2.5 |
| | Information Technology | 1.9 |
| | Other | 1.9 |
| Work experience | 1-2 | 12.8 |
| | 3-10 | 35.4 |
| | 10-20 | 32.3 |
| | 20-30 | 14.0 |
| | 30+ | 6.1 |
| GAI experience | I haven't heard of it | 6.4 |
| | I've heard of it but haven't used it | 38.8 |
| | I have tried but not continued to use it | 22.3 |
| | I use it once a month | 21.7 |
| | I use it once a week | 7.6 |
| | I use it every day | 3.2 |

## 5.2 Acceptance of Generative AI

### Social Influence

The results presented in Table 5 indicate a discrepancy among the respondents' answers. Findings related to the first question indicate that most respondents are inclined to increase their use of GAI if their colleagues would, 20% are neutral or do not know and 24% are inclined to think that it would not affect their use. The rusults related to the second question indicate that most of the respondents (69%) would increase their use of GAI if they were encurages by their manager, 18% are neutral or don't know and a small portion of the respondents do not believed it would affect their usage. Furthermore, results related to the last question suggest that more than two thirds of the respondents (71%) believe that the use of GAI is not considered prestigious in social circles.

**Table 5.** Results related to Social Influence

| If my colleagues increased their use of generative AI, so would I | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree (1) | Disagree | Partly disagree | Neutral (4) | Partly agree | Agree | Fully agree (7) | 4.5 |
| 4% | 11% | 9% | 20% | 26% | 15% | 15% | |

| I would increase my use of generative AI if my boss encouraged me to | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | 5.1 |
| 4% | 3% | 8% | 18% | 22% | 24% | 23% | |

| Using generative AI is seen as prestigious in my social circles | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | 2.6 |
| 36% | 18% | 17% | 19% | 3% | 4% | 2% | |

## Hedonic Motivation

The results related to the first Hedonic Motivation-related question, presented in Table 6, indicate that most respondents do not have a strong opinion whether the use of GAI is entertaining or not, where almost one third of the respondents are neutral (27%), representing the most common answer. The results from the second question indicate that half of the respondents (50%) believe that the use of GAI is satisfying in the presence of positive effects in their work. Furthermore, the result related to the last question indicates that most respondents (71%) are skeptical of GAI in the absence of positive effects in work.

**Table 6.** Results related to Hedonic Motivation

| Using generative AI is entertaining | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | 4.0 |
| 11% | 10% | 14% | 27% | 18% | 11% | 9% | |

| Using generative AI is satisfying when it clearly contributes positive effects in my work | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | 4.4 |
| 11% | 9% | 11% | 21% | 19% | 13% | 18% | |

| I would use generative AI even if it did not contribute clearly positive effects in my work | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | 2.4 |
| 40% | 25% | 16% | 7% | 3% | 3% | 5% | |

## Anthropomorphism

The first results related to the last construct in the primary appraisal, presented in Table 7, indicate that most respondents (70%) do not feel that GAI has its own emotion. However, the findings also indicate that the idea that GAI could possess its own opinions is not entirely dismissed, with only 27% being completely convinced. The findings related to the second question indicate that more than half of respondents (56%) fully reject the idea that GAI has feelings and that the rest of the respondents (44%) do not. The last results related to Anthropomorphism indicate that the respondents are more uncertain about the idea that generative will have its own consciousness in the future than they were in the two previous cases. With a response distribution more towards neutral and only 20% fully reject the statement, this indicates that most of the respondents do not reject such an idea.

**Table 7.** Results related to Anthropomorphism

| | Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | Average |
|---|---|---|---|---|---|---|---|---|
| **I feel that generative AI has its own opinions** | 27% | 14% | 29% | 16% | 7% | 6% | 1% | 2.9 |
| **I feel that generative AI has feelings** | 56% | 13% | 16% | 11% | 2% | 1% | 1% | 2.0 |
| **In the future, generative AI will have a consciousness of its own** | 20% | 14% | 20% | 22% | 10% | 8% | 6% | 3.3 |

## Performance Expectancy

Presented in Table 8, findings related to the first construct in the secondary appraisal indicate, among other things, that half of the respondents do not feel that GAI provides more consistent answers than humans, while about a third do (30%). The findings also indicate that most of the respondents believe that GAI does not generate more accurate information than humans (51%) and that approximately one third (30%) are neutral. The last results indicated great skepticism among respondents, with 64% believing that GAI does not prove as reliable a service as humans do.

**Table 8.** Results related to Performance Expectancy

| | Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | Average |
|---|---|---|---|---|---|---|---|---|
| **Generative AI provides more consistent answers than humans** | 15% | 14% | 21% | 20% | 15% | 9% | 6% | 3.6 |
| **Generative AI generates more accurate information (fewer errors) than what humans generate** | 12% | 17% | 22% | 30% | 9% | 5% | 5% | 3.4 |
| **Generative AI provides more reliable services than humans do** | 20% | 22% | 22% | 22% | 6% | 4% | 4% | 3.0 |

## Perceived Effort Expectancy

The results presented in Table 9 indicate that the respondents are relatively optimistic about the effort in terms of learning how to use GAI, with more than two thirds (72%) suggesting that it does not take too long. Similarly, most respondents (71%) tend to disagree with the idea that the use of GAI is too time consuming. Results also indicate that there is a discrepancy among the respondents in terms of inventiveness, with almost half of the respondents (44%) having a somewhat good understanding of how to use GAI in daily tasks and other 56% not.

**Table 9.** Results related to Perceived Effort Expectancy

| | Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | Average |
|---|---|---|---|---|---|---|---|---|
| **Learning how to use generative AI takes too long** | 18% | 29% | 25% | 15% | 10% | 2% | 1% | 2.8 |
| **It is too time consuming to use generative AI** | 20% | 33% | 18% | 20% | 4% | 2% | 3% | 2.7 |
| **It is difficult to understand how to use generative AI in daily tasks** | 6% | 20% | 18% | 20% | 15% | 9% | 12% | 3.9 |

## Emotion

The results related to the last construct in the primary appraisal, presented in Table 10, indicate that GAI generally does not evoke any strong feelings in the respondents. Findings indicate that most of respondents (82%) either feel that using GAI makes them slightly stressed (23%), neutral (46%) or somewhat relaxed (13%). In addition, 78% of respondents feel that it either makes them feel slightly dissatisfied (12%), Neutral (43%) or slightly satisfied (23%). Similarly, findings related to the last questions do not offer any major evidence that the use of GAI bring any stronger feelings, with 71% of the respondents believing that using it makes them feel slightly desperate (17%), neutral (44%) or slightly hopeful (20%).

**Table 10.** Results related to Emotion

| Using generative AI makes me feel… | | | | | | | Average |
|---|---|---|---|---|---|---|---|
| Stressed | Moderately stressed | Slightly stressed | Neutral | Slightly relaxed | Moderately relaxed | Relaxed | 3.9 |
| 4% | 7% | 23% | 46% | 13% | 3% | 5% | |
| **When I use generative AI, I feel** | | | | | | | **Average** |
| Dissatisfied | Mod. dissatisfied | Slightly dissatisfied | Neutral | Slightly satisfied | Moderately satisfied | Satisfied | 4.1 |
| 3% | 9% | 12% | 43% | 23% | 4% | 6% | |
| **Generative AI makes me feel** | | | | | | | **Average** |
| Desperate | Mod. desperate | Slightly desperate | Neutral | Slightly hopeful | Moderately hopeful | Hopeful | 4.1 |
| 5% | 5% | 17% | 44% | 20% | 4% | 7% | |

## Willingness to Accept the Use of AI

Findings related to the first construct in the outcome stage, presented in Table 11, indicate an overall optimism among respondents in terms of willingness to use GAI. Results show that most of the respondents (65%) lean towards being willing to learn how to use GAI in their work, of which more than a third feel completely confident about it (36%). Similarly, but with slightly greater skepticism, almost half of the respondents (48%) would like to use GAI in their work to a greater extent than they do today, with 29% completely convinced about it. Furthermore, results related to the last question indicate that most respondents (61%) are positive to the idea that they probably will start using GAI in their work, of which almost a third are absolutely sure (31%).

**Table 11.** Results related to Willingness to Accept the Use of AI

| | Fully disagree | Disagree | Partly disagree | Neutral | Partly agree | Agree | Fully agree | Average |
|---|---|---|---|---|---|---|---|---|
| I am willing to learn how to use generative AI in my work | 4% | 3% | 7% | 11% | 18% | 21% | 36% | 5.4 |
| I would like to use generative AI in my work more than I do today | 7% | 11% | 11% | 13% | 14% | 15% | 29% | 4.8 |
| It is likely that I will start using generative AI in my work | 5% | 8% | 12% | 14% | 14% | 16% | 31% | 5.0 |

## Objection to the Use of AI

Results relating to the last construct in the outcome stage, presented in Table 12, indicate a split opinion among the respondents. Firstly, results indicate that most respondents (42%) prefer other sources of information before GAI while a large, but not equally large, number of respondents (31%) prefer GAI. Similarly, results indicate that most respondents (40%) believe GAI processes information in a less humanized way while about one third of the respondents (29%) believe the opposite. Lastly, results indicate that almost all respondents (82%) prefer human contact in service transactions, of which 51% were completely convinced about it, leading to the answer with the highest consensus so far.

**Table 12.** Results related to Objection to the Use of AI

| | Fully agree | Agree | Partly agree | Neutral | Partly dissagree | Disagree | Fully dissagree | Average |
|---|---|---|---|---|---|---|---|---|
| I prefer to use other sources of information over generative AI | 14% | 10% | 18% | 27% | 10% | 15% | 6% | 3.8 |
| Generative AI processes the information in a less humanized way | 2% | 9% | 18% | 29% | 13% | 12% | 15% | 4.4 |
| I prefer human contact in service transactions | 1% | 2% | 5% | 10% | 13% | 18% | 51% | 5.9 |

# 5.2.1 Measurement model assessment

To ensure that the collected data was of good quality, a CFA analysis of the measurement model was carried out. The analysis consisted of several parts which were analysed with SPSS, SPSS AMOS and Excel. The normality of the measurement items within each construct was first checked, where a rule of thumb is that the skewness and kurtosis should be less than two (Hair et al., 1998). The results indicated that the collected data lived up to the criterion in all cases. Furthermore, the constructs' Cronbach's Alpha

and items loading were analysed to check the collected data regarding its internal consistency reliability. The results, displayed in table 13, show that all constructs except Objection to use (O) had a Cronbach Alpha higher than the suggested limit of 0.70, indicating an accepted internal consistency reliability (Hair, Ringle & Sarstedt, 2011). All item loadings were greater than 0.5 except O1 which was 0.310. Suggested cut-off levels vary in the research, where Steven (2002) believes that item loadings should be above 0.4 for interpretation purposes, Hair et al. (2009) above 0.5 but preferably above 0.7, meaning that the construct is explaining 25 or 50 percent or more of the variation in the observed variable (Malhotra, 2010). This means that all loadings except O1 show at least an accepted internal convergent validity, and that half of the item loadings reach the ideal limit of 0.7; indicating an overall acceptable model fit. Furthermore, constructs' convergent validity was examined by analysing their average variance extracted (AVE) values. The results, displayed in Table 13, indicate that Hedonic Motivation, Anthropomorphism, Performance Expectancy and Objection of use do not quite reach the proposed cut-off limit of 0.5, which indicates a questionable convergent validity of those constructs (Fornell & Larcker, 1981).

**Table 13.**
Measurement scale properties

| Construct/Item | Item loading | Cronbach's Alpha | AVE |
|---|---|---|---|
| Social Influence (SI) | | 0.74 | 0.54 |
| SI1 | 0.805 | | |
| SI2 | 0.703 | | |
| SI3 | 0.686 | | |
| Hedonic Motivation (HM) | | 0.77 | 0.47 |
| HM1 | 0.726 | | |
| HM2 | 0.667 | | |
| HM3 | 0.660 | | |
| Anthropomorphism (A) | | 0.86 | 0.40 |
| A1 | 0.585 | | |
| A2 | 0.674 | | |
| A3 | 0.636 | | |
| Performance Expectancy (PE) | | 0.93 | 0.33 |
| PE1 | 0.572 | | |
| PE2 | 0.551 | | |
| PE3 | 0.607 | | |
| Effort Expectancy (EE) | | 0.89 | 0.63 |
| EE1 | 0.798 | | |
| EE2 | 0.803 | | |
| EE3 | 0.773 | | |
| Emotion (E) | | 0.93 | 0.74 |
| E1 | 0.870 | | |
| E2 | 0.858 | | |
| E3 | 0.857 | | |
| Intention to Use (I) | | 0.90 | 0.67 |
| I1 | 0.817 | | |
| I2 | 0.796 | | |
| I3 | 0.844 | | |
| Objection to Use (O) | | 0.60 | 0.24 |
| O1 | 0.315 | | |
| O2 | 0.567 | | |
| O3 | 0.557 | | |

To validate the constructs' discriminant validity, squared roots of AVEs correlation between themselves and the other constructs were analysed, where the former must be greater than the latter for a desired fit (Hair et al., 2014). The results, presented in table 14, indicate that Performance Expectancy has a higher correlation with Anthropomorphism, Emotion and Objection to use than with itself, and that Objection to use has a higher correlation with Anthropomorphism, Performance Expectancy, Effort Expectancy and emotion than with itself, indicating a questionable fit. These results suggest that there is uncertainty about whether the identified constructs measure the same underlying concept (Hair et al., 2014).

**Table 14.**
Discriminant validity (correlation between construct and square roots of AVE)

| Construct | SI | HM | A | PE | EE | E | I | O |
|---|---|---|---|---|---|---|---|---|
| Social Influence (SI) | (0.733) | | | | | | | |
| Hedonic Motivation (HM) | 0.440 | (0.685) | | | | | | |
| Anthropomorphism (A) | 0.036 | 0.440 | (0.633) | | | | | |
| Performance expectancy (PE) | 0.090 | 0.373 | 0.632 | (0.577) | | | | |
| Effort expectancy (EE) | -0.179 | 0.035 | 0.585 | 0.578 | (0.791) | | | |
| Emotion (E) | 0.067 | 0.411 | 0.529 | 0.687 | 0.498 | (0.862) | | |
| Intention to use (I) | 0.465 | 0.523 | 0.189 | 0.387 | 0.082 | 0.426 | (0.819) | |
| Objection to use (O) | -0.188 | 0.155 | 0.524 | 0.671 | 0.691 | 0.580 | 0.238 | (0.494) |

Finally, the global fit of the measurement model was investigated. First, the Comparative Fit Index (CFI) and the Tucker Lewis Index (TLI) were analysed. The results indicated that the model's CFI was 0.94 and that the TLI was 0.93, which is slightly below the cut-off limit of 0.95, indicating that the model is very close to a good fit (Hu & Bentler, 1999). Furthermore, the Root Mean Square Error of Approximation (RMSEA) was analysed and found to be 0.066, indicating an acceptable model fit (Hu & Bentler, 1999; Steiger, 2007). Finally, the Chi-square value, degrees of freedom and ratio between these were examined. The results showed a Chi-square value of 384.04 with 224 degrees of freedom, leading to a ratio of 1.71, which is below the recommended value of 3 and thus an indication of a good model fit (Kline, 2005).

### 5.2.2 Structural Model assessment

After the CFA analysis, which both signalled a good measurement model fit through some measures and questionable through others, a maximum likelihood estimation-based CB-SEM was carried out with the tool SPSS AMOS. The first step was to examine the fit of the structural model, where the results showed a Chi-square value of 504.00 with 239 degrees of freedom, which means a Chi-square to Degrees of freedom of 2.11, which is lower than 3 and thus evidence of a good fit. Furthermore, the CFI and TLI for the structural model were examined, which were found to be 0.90 and 0.89, indicating questionable fit as it is below the cut-off level of 0.95. Finally, the RMSEA was examined, which was found to be 0.082, which exceeds the upper consensus limit of 0.7 (Steiger, 2007).

The results of the CB-SEM, which are presented in Illustration 2, indicate several different. The results indicate that Hedonic Motivation was negatively related to Perceived Effort Expectancy (β = -.25, p < .05). Anthropomorphism was positively related to Performance Expectancy (β = .64, p < .001) as well as Perceived Effort Expectancy (β = .74, p < .001. Furthermore, Performance Expectancy was found to be positively related to Emotion (β = .62, p < .001). Perceived Effort Expectancy was found to be weakly positively related to Emotion. Finally, Emotion was found to be positively related to both Willingness to Accept the Use of AI Devices (β = .43, p < .001), as well as Objection to the Use of AI Devices (β = .66, p < .001). In addition to the significant relationships, some of the relationships were found to be non-significant. Social Influence was weakly positively non-significantly related to Performance Expectancy. The same construct was found to have a weakly negative non-significant relationship with Perceived Effort Expectancy. Also, Hedonic Motivation was found to be negatively non-significantly related to Perceived Effort Expectancy.

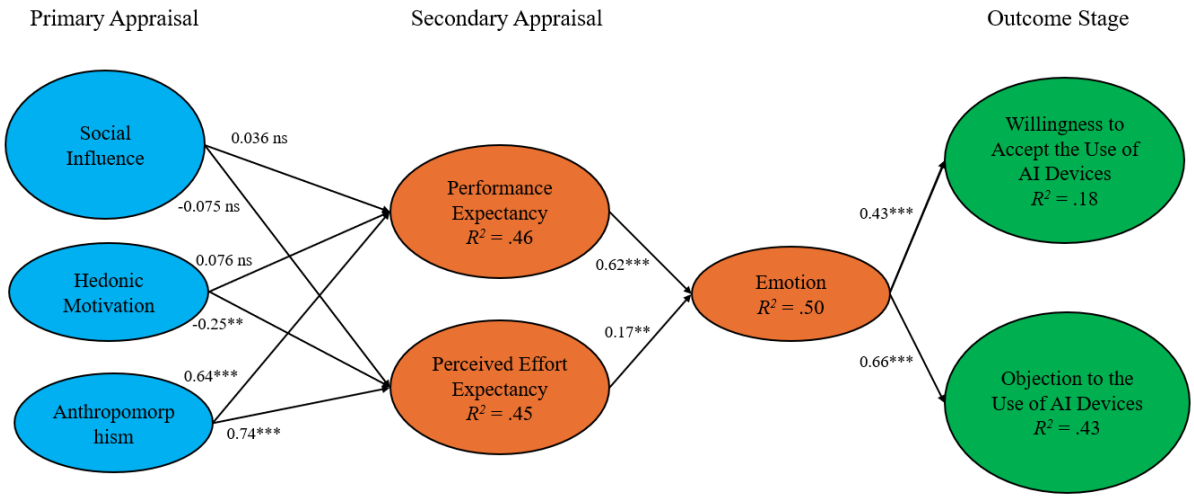


**Illustration 2**. Authors results of CB-SEM. *** p < .001; ** p < .05

In the development of the questionnaire, the degree scale associated with question Q21 mistakenly became inverted so that “1” indicated "Fully agree" instead of "Fully disagree" and “7” "Full disagree" instead of "Fully agree". The error was noticed after all responses were collected and was chosen not to be excluded. This is reasonably the reason for the low loading of O1 presented in Table 13, as well as the Cronbach Alpha associated with the construct Objection to the Use of AI. When excluding this question, no noticeable differences in model fit could be identified.

## 5.3 Areas of Application

The results regarding the second research question indicate a wide range of identified tasks that can potentially be performed using tools built on GAI. In addition to these, tasks are also presented that

respondents are more skeptical about. The respondents' answers to each question are categorized under five areas, and within these further categorizations could be carried out in many cases. The five different areas that were identified were Communication and Language Processing, Research and Analysis, Legal Matters and Contracts, Business and Management, and Administration and Document Management.

### 5.3.1 Tasks generative AI can function as support in

The results from the survey study's first open-ended question indicate that GAI has a very broad spectrum of use within the context of property management. Among the 114 respondents who answered the first question, it was possible to roughly distinguish 68 different tasks which, after structuring, could be categorized within the 5 different areas in which the respondents identified use of GAI. The most common type of tasks is displayed in Table 15 and the full list in Appendix 2.

**Communication and Language Processing**

Of all the tasks identified by the respondents, 42.3% of these could be sorted under the category Communication and Language Processing, comprising a total of 13 different tasks. The most common type of tasks could further be sorted under Text processing (20.9%) which included tasks such as Formulating texts (8.5%), Drafting emails (8.0%) and Compile text (3.0%) among others. The second most common type of tasks could be categorized under Advertising (11.9%), comprising tasks such as Advertising (3.5%), Information letters and Presentations (3.0%). Furthermore, communication (e.g. Communication with tenants) and translation (4.5%) were identified as tasks that can be supported by GAI.

**Research and Analysis**

Among the respondents' suggestions, 27 types of tasks, constituting 27.4% of the respondents' total suggestions, were categorized under Research and Analysis. The most common type of work tasks fell under Analysis, which consisted of tasks such as Analysis (3.5%) and Interpretation and analysis of property-related documents (1.5%) among many more. The second most common types of tasks were categorized under Creative tasks and included, for example, Idea generation (1.0%) and Image generation (1.0%). Several tasks were also identified in areas such as Data management (e.g. Coding, Statistical basis, Compile data), Due diligence (e.g. Answer questions, Review questions) and Research (e.g. Information gathering, Background check).

**Legal Matters and Contracts**

Furthermore, four types of tasks, constituting 10.4% of all the respondents' suggestions, were categorized under Legal Matters and Contracts. The most common suggestions were Contractual Issues (5.0%) and Legal Matters (4.0%), followed by Negotiations (1.0%) and Invoice management (0.5%).

**Business and Management**

The penultimate category of tasks that was identified was Business and Management, which contained 14 types of tasks constituting 10.0% of all the respondents' proposals for tasks. The most common type of task was facilitating tasks, which included tasks such as Proposals for new routines (1.5%) and Notifications (0.5%). Information was also identified within Rental, such as Rental sketches (1.5%) and Property descriptions (0.5%). Other common tasks were categorized under Business (e.g. Finance, Assess profitability in business) and Management (e.g. Maintenance plans).

**Administration and Document Management**

The last category of tasks that was identified was Administration and Document Management, which contains 10 types of tasks constituting 10.0% of all the respondents' suggestions for tasks. The most common tasks are categorized under Administrative tasks, which included Administrative tasks (2.5%) and Create lists (0.5). Tasks within Documentation (e.g. Fault reports, Protocols) and Document management (e.g. Fill in templates, Archiving) were also identified.

**Table 15.**
Tasks Generative AI can function as support in

| Type | Task | Occurrence (%) |
|---|---|---|
| **Communication and Language Processing** | | **42.3** |
| | Text processing | 20.9 |
| | Advertising | 11.9 |
| | Communication | 5.0 |
| | Translation | 4.5 |
| **Research and Analysis** | | **27.4** |
| | Analysis | 9.0 |
| | Creative tasks | 4.5 |
| | Data management | 3.5 |
| | Due diligence | 3.5 |
| | Research | 3.5 |
| | Other | 3.5 |
| **Legal Matters and Contracts** | | **10.4** |
| | Contractual Issues | 5.0 |
| | Legal matters | 4.0 |
| | Negotiations | 1.0 |
| | Invoice management | 0.5 |
| **Business and Management** | | **10.0** |
| | Facilitating tasks | 3.0 |
| | Rental | 2.5 |
| | Business | 2.5 |
| | Management | 2.0 |
| **Administration and Document Management** | | **10.0** |
| | Administrative tasks | 3.5 |
| | Documentation | 3.5 |
| | Document management | 3.0 |

## 5.3.2 Tasks that Generative AI can perform on its own

The results from the survey study's second open-ended question indicate that GAI has a wide range of uses within the context of tasks in property management that the technology can handle without or

almost without supervision. Of the total of 95 suggestions from the respondents, 34 unique tasks were identified, of which the most common are presented in Table 16 and the full list in Appendix 3. The same categorization was used as in the analysis of the first open-ended question.

**Communication and Language Processing**

Of all the tasks that the respondents identified as completely or almost being able to be performed by GAI, 49.5% were sorted under the category Communication and Language Processing, comprising a total of 10 different tasks. The most common type of nav tasks was Text processing, where tasks such as Drafting emails (13.7%), Formulating texts (3.2%) and Summaries (3.2%) were suggested. Furthermore, three tasks could be sorted under Communication, such as Communication with tenants (9.5%) and FAQ (2.1%). Tasks within Advertising (e.g. Information letters, Presentations) and Translation (4.2%) were also suggested.

**Research and Analysis**

Among the respondents' suggestions, 11 types of tasks, constituting 18.9% of the respondents' total suggestions, were categorized under Research and Analysis. The most common tasks were within analysis, where, among other things, Forecasts (2.1%), Consumption (1.1%) and Operational optimization of properties (1.1%) were addressed. Information gathering (6.2%) was proposed as well as three tasks within Data management (e.g. Calculations, Coding).

**Legal Matters and Contracts**

Furthermore, four types of tasks, constituting 12.6% of all the respondents' suggestions, were categorized under Legal Matters and Contracts. The identified tasks were Lease agreements (5.3%), Invoice management (3.2%), Contracts (2.1%) and Legal issues (2.1%).

**Administration and Document Management**

One of the least frequent tasks was those categorized under Administration and Document Management, which contained four types of tasks constituting 10.5% of all the respondents' proposals for tasks. The most suggested work task was Fault reports (6.3%), followed by Administrative tasks (2.1%), Digital readings (1.1%) and Protocols (1.1%).

**Business and Management**

The least common type of use areas identified was Business and Management, which contain 5 types of tasks constituting 8.4% of all the respondents' suggestions for tasks. The most common work tasks that were mentioned were Vacancy descriptions (3.2%) and business-related tasks such as Budget issues (2.1%) and Bidding (1.1%). Draft maintenance plans for properties (1.1%) and Planning (1.1%) also occurred.

**Table 16.**
Tasks that Generative AI can largely perform on its own

| Type | Task | Occurrence (%) |
|---|---|---|
| **Communication and Language Processing** | | **49.5** |
| | Text processing | 20.0 |
| | Communication | 13.7 |
| | Advertising | 11.6 |
| | Translation | 4.2 |
| **Research and Analysis** | | **18.9** |
| | Analysis | 7.4 |
| | Information gathering | 6.3 |
| | Data management | 3.2 |
| | Image generation | 1.1 |
| | Report Writing | 1.1 |
| **Legal Matters and Contracts** | | **12.6** |
| | Lease agreements | 5.3 |
| | Invoice management | 3.2 |
| | Contracts | 2.1 |
| | Legal issues | 2.1 |
| **Administration and Document Management** | | **10.5** |
| | Fault reports | 6.3 |
| | Administrative tasks | 2.1 |
| | Digital readings | 1.1 |
| | Protocols | 1.1 |
| **Business and Management** | | **8.4** |
| | Vacancy descriptions | 3.2 |
| | Business | 3.2 |
| | Draft maintenance plans for properties | 1.1 |
| | Planning | 1.1 |

### 5.3.3 Tasks that cannot be solved using Generative AI

The results from the survey study's third open-ended question indicate that there are a number of tasks the respondents consider difficult to solve by GAI and which they therefore cannot see the use of the tools within. Of the total of 133 proposals, 31 unique tasks could be identified, of which the most common is presented in Table 17 and the full list in Appendix 4. The categorization was somewhat different compared to one used in the first and second open-end questions due to different answers from respondents.

**Communication**

Of the respondents' suggestions for work tasks that GAI cannot contribute with support within, 54.1% were sorted under the category Communication, comprising a total of 8 different tasks. Among the data that suggested that, by far the most common answers were Customer contact (32.3%) followed by Human interaction (16.5%). In addition to these two, information such as Phone contact (1.5%), Long emails (0.8%) and Personal emails (0.8%) were mentioned among others.

### Legal Matters and Contracts

Among the respondents' suggestions, four types of tasks, constituting 18.8% of the respondents' total suggestions, were categorized under Legal Matters and Contracts. The task that the respondents were most united in that GAI cannot assist with support within is Negotiations (12.8%). In addition, Agreements (3.9%), Legal tenancy issues (1.6%) and Invoice management (0.8%) were also suggested.

### Business and Management

Furthermore, 11 types of tasks suggested not able to be performed by GAI, constituting 12.8% of all the respondents' suggestions, were categorized under Business and Management. The most common tasks could be categorized under Management, which included, among other things, Inspections (2.3%), Leadership (2.3%) and Maintenance checks (1.5%). Information related to rental was also identified, such as Apartment/venue viewing (5.3%) and Change the name of the apartment door and entrance (0.8%). The least frequent tasks were business related, where Budget issues (0.8%) and Rent levels (0.8%) were suggested.

### Research and Analysis

The category of tasks that was the least frequent was Research and Analysis, which contained three types of tasks constituting 5.3% of all the respondents' suggestions for tasks. The identified tasks were Problem solving (2.3%), Calculations (1.5%) and Creative tasks (1.5%).

### Other tasks

The respondents' answers could not in all cases be categorized under the suggested categories. These were Assessment of people's prestige (0.8%), Evacuation in case of fire (0.8%), Fun tasks (0.8%), Responsiveness (0.8%) and Updates (0.8%).

**Table 17.**

Tasks that Generative AI can largely perform on its own

| Type | Task | Occurrence (%) |
|---|---|---|
| **Communication** | | **54.1** |
| | Communication | 54.1 |
| **Legal Matters and Contracts** | | **18.8** |
| | Negotiations | 12.8 |
| | Agreements | 3.8 |
| | Legal tenancy issues | 1.5 |
| | Invoice management | 0.8 |
| **Management and Finance** | | **18.0** |
| | Management | 10.5 |
| | Rental | 6.0 |
| | Business | 1.5 |
| **Research and Analys** | | **5.3** |
| | Problem-solving | 2.3 |
| | Calculations | 1.5 |
| | Creative tasks | 1.5 |
| **Other** | | **3.8** |
| | Assessment of people's prestige | 0.8 |

| | |
|---|---|
| Evacuation in case of fire | 0.8 |
| Fun tasks | 0.8 |
| Responsiveness | 0.8 |
| Updates | 0.8 |

# Chapter 6

# Discussion

*The purpose of this study was to contribute to the limited research on generative AI within the context of the property management industry, with the hope of providing insights to Swedish real estate management companies. To fulfill the purpose of the study, two different questions were formulated, one of which examined the socio-technical aspects surrounding the acceptance of generative AI, and the other the technical aspects surrounding its use. Through a survey study and subsequent analysis, several findings could be identified, which together answered the study's questions. This discussion section aims to explain the findings and their relationship to the existing knowledge in the field.*

## 6.1 Acceptance of Generative AI

The first research question aimed to bring an idea about the factors that lead to a user of GAI either accepting the technology or rejecting it. By exploring the reasons for acceptance or rejection, the question aimed to provide guidance to real estate management companies, employees and managers who wish to implement GAI in their operations, processes and daily tasks. By formulating and analysing 24 questions, collected through an internet-based survey study with a total of 172 participating respondents, through the AI Device Use Acceptance model by Gursoy et al. (2019), several findings could be identified.

**Primary appraisal: Social Influence, Hedonic Motivation and Anthropomorphism**

The findings related to the first construct in the primary appraisal of the AIDUA model, Social Influence, suggest that the degree to which colleagues use GAI has minimal positive influence on an individual's

personal use of GAI. However, it turned out that encouragement from managers has a slightly greater impact. In addition to this, the findings suggest that the use of GAI is not significantly associated with prestige in social circles. Furthermore, findings related to the second construct in the primary appraisal, Hedonic Motivation, suggest that using GAI is not perceived as either entertaining or boring, but when it proves helpful in tasks, it becomes somewhat satisfying. If it weren't for its demonstrated usefulness, findings suggest that it would likely not be used, but with little hesitation. The findings related to the last construct in the primary appraisal, Anthropomorphism, suggest that the idea that GAI could possess its own opinions, feelings, and consciousness in the future is not entirely dismissed.

**Secondary appraisal: Performance Expectancy, Perceived Effort Expectancy and Emotion**

Furthermore, findings related to the first construct in the secondary appraisal of the AIDUA model, Performance Expectancy, suggest that outputs from GAI are perceived to be somewhat less consistent than those from humans, and that they also contain slightly more errors. Additionally, services delivered by GAI tools are considered to be less reliable than those delivered by humans. Findings related to the second construct in the secondary appraisal, Perceived Effort Expectancy, suggest that learning how to use GAI is not considered very difficult, nor is it perceived as time-consuming to use. The last findings related to the secondary appraisal, concerning the emotion construct, suggest that the use of GAI has small to none impact on users' emotions.

**Outcome Stage: Willingness to Accept the Use of AI and Objection to the Use of AI**

Furthermore, findings related to the first construct in the outcome stage of the AIDUA model, Willingness to Accept the Use of AI, suggest that there is a desire to learn more about GAI and how it can be used in their profession. In addition, findings related to the last construct, Objection to the Use of AI, suggest that, as an information source, GAI is perceived to be marginally inferior to human sources, but within service transactions, human-to-human interaction is clearly more desirable.

**Relationships between constructs**

The findings from the CB-SEM analysis indicate several different discoveries, the first of which is that Hedonic Motivation is negatively related to Perceived Effort Expectancy, which suggests that the more motivated a user are, the more likely it is that they will find the use of GAI more effortless. This is in line with other studies where the AIDUA model has been applied (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020), with the only difference that the relationship turned out to be somewhat weaker in this study. The reason for the somewhat weaker negative relationship could maybe be explained by the different contexts, where this study investigates employees' acceptance of GAI in their work and the other studies customers' acceptance of AI in service. The result could thus indicate that motivation has less importance within a workplace context than a service context, possibly because the

use is experienced more as a duty in the former as opposed to the latter where it is perhaps more about convenience.

Furthermore, findings also indicate that Anthropomorphism was positively related to Performance Expectancy as well as Perceived Effort Expectancy, which suggest that user's degree of experienced anthropomorphism will have a positive influence on the perceived performance but also on the effort, e.g. if a user perceives the GAI tool to have human-like characteristics, they will expect it to perform well, but also to require more engagement. The scenario could be explained by the assumption that a user has trust in humans, and thus believes that GAI tools are more reliable the more similar they are to a human. However, this effect comes at the expense of increased perceived effort. That Anthropomorphism would have a negative relationship with Perceived Effort Expectancy is in line with previous research (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020), however, the relationship was almost twice as large in this study, which can perhaps be explained by the fact that the context difference. That Anthropomorphism would have a positive relationship with Performance Expectancy is a unique finding compared to earlier studies.

Performance Expectancy was found to be positively related to Emotion, suggesting that the stronger a user's belief is in the effectiveness of tools built on GAI, the more positive emotions they will experience. This result is completely in line with previous findings (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020) with a normally strong relationship. Furthermore, Perceived Effort Expectancy was found to be weakly positively related to Emotion, suggesting that the more difficult a user thinks the use of GAI is, the more positive emotions they will experience. This finding could indicate that even though the use of GAI is perceived as more difficult or time-consuming, there is still a sense that it may be worth the effort; that the work required is outweighed by the expected benefits, thus leading to positive emotions. This result stands out in the crowd compared to previous studies (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020) where a weak negative relationship was identified, as well as a non-significant minimally negative relationship within the context of full-service hotels (Lin, Chi & Gursoy, 2020).

Finally, Emotion was found to be positively related to both Willingness to Accept the Use of AI Devices, as well as Objection to the Use of AI Devices. These findings indicate that positive emotions both lead users to accept but also refrain from using GAI, where the first is in line with previous studies (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020) and the latter is a new finding. This finding could potentially be explained by the fact that a user does not only feel one thing at a time, i.e. they can both want to use something and at the same time not want it at all. An example of this in another context could be that you want your loved one to go away and have a nice trip abroad because it will make them happy, but at the same time you don't want them to go at all because it means they leave you in a whole

month. In summary, these findings may possibly reflect that people do not think black or white, but there is much more in between.

**Non-significant relationships between constructs**

Some of the relationships were found to be non-significant. Social Influence was found to be weakly positively non-significantly related to Performance Expectancy, suggesting that social influences do not affect a user's view of whether GAI performs well or not. The same construct was found to have a weakly negative non-significant relationship with Perceived Effort Expectancy, indicating that it also does not impact a user's perceived effort of using GAI, thus suggesting that Social Influence has no association with acceptance of GAI whatsoever. These findings are partly in line with previous research (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020) where a relationship between Social Influence and Perceived Effort Expectancy has not been identified, but a weak relation between the previous and Performance Expectancy. The difference in the findings of to this study could be explained by the context difference, where one's social circles possibly have no influence on which processes and tools one uses at work in comparison to which type of service one chooses in one's free time. Another explanation could be that social influence slowly but surely ceases to be important, which in turn can possibly be explained by all the media exposure and an increased acceptance of the idea that everyone is different and thinks differently.

Lastly, Hedonic Motivation was found to be non-significantly negatively related to Perceived Effort Expectancy, suggesting that regardless of whether a user is motivated or not, it will not impact the perceived effort of using GAI; which could either indicate that the two have no connection or that the usage is perceived as a duty or necessity, and thus it does not matter whether they perceive it as difficult or not. This finding differs from previous research (Gursoy et al., 2019; Lin, Chi & Gursoy, 2020; Roy et al., 2020) where a positive relationship was found. The explanation for the difference between this study's findings and the previous ones could also lie in the difference in context, where more motivation is required to use an AI in service, which by the way is completely voluntary and if you don't like it, you can change hotels etc., than it does in work, where it is possibly seen as a threat to fall behind in usage.

## 6.2 Areas of Application

The second research question aimed to explore which specific tasks employees in the property management industry have identified within their daily responsibilities, with the hope to provide insights to professionals within the industry. The results indicated a long list of potential tasks that GAI can both support in, fully or partially manage without human supervision, and that cannot be performed with generative AI.

### 6.2.1 Tasks Generative AI can function as support in

The most recurring tasks were identified under the Communication and Language Processing category, where Text processing-related tasks were most frequent. Formulating texts, which was a common suggestion from respondents, is a suggestion that can include a series of tasks that GAI can act as support within. For example, it could be about using GAI to write a detailed description of a new property improvement, where the AI potentially, in quickly manner, generate a professional text that describes the project's purpose, implementation and expected benefits for the tenants. Another very common task was email drafting, where a GAI tool can quickly and professionally generate an email to a tenant who has reported a maintenance problem, where perhaps information about the next step is explained. Another common task in the Communication and Language Processing category was Translation, where GAI can quickly and accurately generate translations into most languages in a user-selected tonality, which could potentially be particularly valuable for a property manager who needs to communicate with tenants using other mother tongue.

The results in the Research and Analysis category indicated many interesting uses, with Analysis being the most frequent. The term is broad and could mean a long list of applications as GAI can quickly analyze large amounts of data and identify patterns and anomalies. For example, a property manager could use GAI in the analysis of energy consumption over time to identify inefficient use and suggest energy-saving measures, which would reduce operating costs and improve the sustainability profile of the property. Another task, closely related to the previous one, was Interpretation and analysis of property-related documents. Potentially, this could involve using a GAI-powered tool to review new leases and identify important or critical clauses that affect the terms of the lease, potentially giving the property manager a better understanding of the contract and reducing the risk of missing something important. Another task that occurred was Information gathering, which from a property manager's perspective could possibly involve using a GAI-driven tool in the collection of data on, for example, market rents, vacant properties and economic trends in order to, which could potentially lead to competitive advantage, especially against those who do not use GAI.

Under the category Legal Matter and Contracts, four different tasks were identified, of which Contractual issues were the most common. In addition to potentially assisting in the process of identifying important and critical clauses in leases, GAI could potentially help a property manager identify rent amounts, renewal clauses and maintenance responsibilities, and compare these to standard contracts and identify any discrepancies. Furthermore, the second most frequent task was Legal matters, which could mean that a property manager uses GAI in the analysis of local building regulations, where the AI can potentially quickly and accurately summarize their impact on renovation projects.

Within the Business and Management category, among other things, Proposals for new routines and Rental sketches were identified as tasks in which the respondents see potential use of GAI. An example

of the former could potentially be explaining one's current property management routines to a GAI utility and asking it to analyze and suggest new routines. An example of the latter would possibly be to let a GAI tool generate a detailed proposal for e.g. furnishing or renovation possibilities, with the hope of giving potential tenants a better idea of an apartment's potential.

Within the last category, Administration and Document Management, a number of different tasks were identified, where Administrative tasks and Fault reports were the most common. Administrative tasks may appear to be a broad term that includes a range of different tasks. A potential example could be for a property manager to connect a GAI-powered tool to their email and have it automatically send out invoices for rent payments as well as track late payments and update payment statuses; which could possibly reduce the risk of human error and ensure that payments are processed in a timely manner.

Many of the identified uses are in line with those Szumilo & Wiegelmann (2024) highlights in his analysis of AI and LLM's transformative impact on the real estate industry. Szumilo & Wiegelmann (2024) highlights, among other things, that LLM can automate routine customer and tenant communication, which the respondents seem to verify through several answers, such as email drafting, information letters and communication. Tasks such as advertising and sales text are also in line with Szumilo & Wiegelmann (2024), who suggests that LLM's can optimize marketing and sales in property management. Szumilo & Wiegelmann (2024) also suggests that LLM's can be used as an aid in market analysis, which is also suggested by the respondents through answers such as analysis, information gathering and environmental awareness. Bidding has previously been identified as a task performable by GAI in Ghimire, Kim & Acharya (2024). Under the category Legal Matters and Contracts, tasks such as Contractual issues and Legal matters are indicated by respondents as well as by Szumilo & Wiegelmann (2024), who believes that LLM can be used in the review and analysis of legal documents, which is also in line with Moon, Chi & Im (2022) who propose that GAI can automate the detection of contractual risk clauses. Just as Szumilo & Wiegelmann (2024) suggests, respondents' answers also point to a broad set of tasks in documentation and administration.

### 6.2.2 Tasks that Generative AI can perform on its own

The results pertaining to the second question posed to the respondents indicate a wide range of tasks that tools based on GAI can more or less perform without human supervision. Just as in the first question, tasks that can be categorized under Communication and Language processing were most common. Drafting emails was the most common task followed by Communication with tenants, which was discussed in the previous question. In the Advertising subcategory, Information letters and Advertising were most frequent. Examples of GAI application of the first could be to have the AI produce automated and consistent information letters to all tenants about e.g. planned maintenance works on the property, including details of timings, impact and contact details for queries etc., which could potentially save both time and resources and ensure prompt and consistent communication. An example of the latter,

Advertising, could be to let the AI create and publish ads for vacant apartments including good descriptions and possibly AI-generated interior images.

A common task categorized under Research and Analysis was Forecasts, where a property manager could potentially have GAI generate forecasts for next year's rental income based on historical rental data, current market trends and economic indicators. Consumption was also suggested as a suitable task, where GAI could potentially monitor properties' energy consumption and suggest adjustments in e.g. HVAC system. In the Legal Matters and Contracts category, similar tasks were suggested as in the previous question with the exception that negotiations did not occur, suggesting that it is a task that respondents do not believe GAI can handle without supervision.

Within the category Administration and Document Management, Fault reports and Administrative tasks were the most frequent tasks, followed by Digital readings and Protocols. In the context of digital readings, GAI could potentially automatically collect, analyze and report digital metrics from various systems in a property, such as water consumption, temperature and security systems. Within the context of Protocols, one could imagine a property manager letting a GAI tool update e.g. security protocol for a property based on new legal requirements and security standards.

The least frequent category of tasks was Business and Management, where among other things Budget issues and Bidding were suggested. Examples of the former could potentially be having a GAI tool analyze real estate expenses and income and propose budget adjustments, possibly also producing reports such as quarterly updates or the like. Examples of the latter, Bidding, could be that a property manager lets a GAI tool create a tender request document for the renovation of a property, sends it out to a selection of contractors, analyzes received tenders based on e.g. price, quality and timeframes, and then propose which of the tenders is best for the project.

### 6.2.3 Tasks that cannot be solved using Generative AI

When it came to respondents' answers to the last question, the results suggest that Communication is an area they generally seem to be most skeptical about in the context of GAI use. Customer contact and Human interaction were the most common, where the former can be thought to depend on what kind of contact they mean. Customer contact can take place in many ways and the answer can reasonably be interpreted above all as meaning face-to-face contact. Within the Legal Matters and Contracts category, information previously mentioned in the previous questions was proposed, which also indicates a non-agreement among the respondents. Among the tasks, Negotiations was the most common, which together with the findings from the previous question suggest that the respondents have little confidence in GAI's contribution in this area.

Within Business and Management, most tasks that traditionally are performed on-site were suggested, such as e.g. Inspections, Maintenance checks, Reconstructions, site visits and apartment viewing.

Budget issues were also suggested to be something that cannot be carried out with the help of GAI, which indicates a non-agreement between the respondents as budget issues were previously suggested to be carried out by GAI without human supervision. Furthermore, three tasks within Research and Analysis were proposed, all of which can be argued to have been mentioned in the two previous questions.

# Chapter 7

# Conclusion and Future Research

*In this study's last chapter, the study's conclusion is first presented, followed by suggestions for future research.*

## 7.1 Conclusion

This study explored drivers and barriers to the acceptance of generative AI as well as potential uses of this emerging technology in the context of property management. Through a survey study with 172 respondents, drivers and barriers related to acceptance of generative AI were analyzed and discussed through the factors presented in the AI Device Use Acceptance Model by Gursoy et al. (2019). The findings explain the factors that lead to a user of generative AI either accepting the technology or rejecting it, providing guidance to property management companies, employees and managers who wish to implement generative AI in their operations, processes and daily tasks. Furthermore, tasks that generative AI can function as a complement in, are able to perform without or with little supervision and potentially cannot contribute with support within were analyzed and discussed. The findings indicate a wide range of tasks that could potentially be supported by generative AI. These are valuable for property managers with both limited experience with generative AI as well as those with experience. Those who have not tried the technology will get an understanding of the types of tasks that are suitable to be performed by or with the support of generative AI, which hopefully convinces them to take advantage of the technology. Among those already using generative AI, the study's findings can hopefully accelerate their use and make them benefit even more from the technology. The findings pertaining to

both research questions can also be thought to be relevant to other industries and contexts to a large extent.

## 7.2 Future research

This study investigated acceptance of generative AI as well as potential applications of it in the real estate industry. Suggestions for future research could be to examine acceptance at a later stage when generative AI has become more common with the hope of bringing a deeper understanding of how AI acceptance changes over time. It would also be interesting to investigate the risks associated with the use of generative AI, both within the context of property management but also within other relevant contexts. A third suggestion for potential future research could be to investigate through a case study the actual use of generative AI in property management, to bring a deeper understanding of the opportunities and difficulties.

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# Appendices

**Appendix 1.**
Survey question 1-24 translations

| **Primary Appraisal** | |
|---|---|
| Question 1 | **EN**: If my colleagues increased their use of generative AI, so would I.<br>**SE**: Ifall mina kollegor ökade sitt användande av generativ AI så skulle jag också göra det. |
| Question 2 | **EN**: I would increase my use of generative AI if my boss encouraged me to.<br>**SE**: Jag skulle öka mitt användande av generativ AI ifall min chef uppmuntrade mig till det. |
| Question 3 | **EN**: Using generative AI is seen as prestigious in my social circles.<br>**SE**: Användning av generativ AI ses som prestigefyllt i mina sociala kretsar. |
| Question 4 | **EN**: Using generative AI is entertaining.<br>**SE**: Att använda generativ AI är underhållande. |
| Question 5 | **EN**: Using generative AI is satisfying when it clearly contributes positive effects in my work.<br>**SE**: Att använda generativ AI är tillfredställande när det tydligt bidrar med positiva effekter i mitt arbete. |
| Question 6 | **EN**: I would use generative AI even if it did not contribute clearly positive effects in my work.<br>**SE**: Jag skulle använda generativ AI även om det inte bidrog med tydligt positiva effekter i mitt arbete. |
| Question 7 | **EN**: I feel that generative AI has its own opinions.<br>**SE**: Jag upplever att generativ AI har egna åsikter. |
| Question 8 | **EN**: I feel that generative AI has feelings.<br>**SE**: Jag upplever att generativ AI har känslor. |
| Question 9 | **EN**: In the future, generative AI will have a consciousness of its own.<br>**SE**: I framtiden kommer generativ AI ha ett eget medvetande. |
| **Secondary Appraisal** | |
| Question 10 | **EN**: Generative AI provides more consistent answers than humans.<br>**SE**: Generativ AI tillhandahåller mer konsekventa svar än människor. |
| Question 11 | **EN**: Generative AI generates more accurate information (fewer errors) than humans generate.<br>**SE**: Generativ AI genererar mer exakt information (färre fel) än den människor genererar. |
| Question 12 | **EN**: Generative AI provides more reliable services than humans do.<br>**SE**: Generativ AI tillhandahåller pålitligare tjänster än vad människor gör. |
| Question 13 | **EN**: Learning how to use generative AI takes too long.<br>**SE**: Att lära sig använda generativ AI tar för lång tid. |
| Question 14 | **EN**: It is too time consuming to use generative AI.<br>**SE**: Det är för tidskrävande att använda generativ AI. |
| Question 15 | **EN**: It is difficult to understand how to use generative AI in daily tasks.<br>**SE**: Det är svårt att förstå hur man ska använda generativ AI i dagliga arbetsuppgifter. |
| Question 16 | **EN**: Using generative AI makes me feel: Stressed/relaxed.<br>**SE**: Att använda generativ AI gör mig: Stressad/avslappnad. |
| Question 17 | **EN**: When I use generative AI, I feel: Dissatisfied/satisfied.<br>**SE**: När jag använder generativ AI känner jag mig: Missnöjd/nöjd. |
| Question 18 | **EN**: Generative AI makes me feel: Desperate/hopeful.<br>**SE**: Generativ AI får mig att känna mig: Förtvivlad/hoppfull. |
| **Outcome Stage** | |
| Question 19 | **EN**: I am willing to learn how to use generative AI in my work.<br>**SE**: Jag är villig att lära mig hur jag ska använda generativ AI i mitt arbete. |
| Question 20 | **EN**: I would like to use generative AI in my work more than I do today.<br>**SE**: Jag skulle vilja använda generativ AI i mitt arbete mer än vad jag gör idag. |
| Question 21 | **EN**: It is likely that I will start using generative AI in my work.<br>**SE**: Det är troligt att jag kommer börja använda generativ AI inom mitt arbete. |
| Question 22 | **EN**: I prefer to use other sources of information over generative AI.<br>**SE**: Jag föredrar att använda andra informationskällor framför generativ AI. |
| Question 23 | **EN**: Generative AI processes the information in a less humanized way.<br>**SE**: Generativ AI bearbetar informationen på ett mindre humaniserat sätt. |
| Question 24 | **EN**: I prefer human contact in service transactions.<br>**SE**: Jag föredrar mänsklig kontakt vid serviceärenden. |

**Appendix 2.**

Tasks Generative AI can function as support in

| **Communication and Language Processing** | | **(%)** |
|---|---|---|
| **Text processing** | | **20.9** |
| | Formulating texts | 8.5 |
| | Drafting emails | 8.0 |
| | Compile text | 3.0 |
| | Meeting summaries | 1.0 |
| | Summaries | 0.5 |
| **Advertising** | | **11.9** |
| | Advertising | 3.5 |
| | Information letters | 3.5 |
| | Presentations | 3 |
| | Sales texts | 1.5 |
| | Marketing | 0.5 |
| **Communication** | | **5.0** |
| | Communication with tenants | 3.5 |
| | Communication | 1.5 |
| **Translation** | | **4.5** |
| | Translation | 4.5 |
| **Research and Analysis** | | |
| **Analysis** | | **9.0** |
| | Analysis | 3.5 |
| | Interpretation and analysis of property-related documents | 1.5 |
| | Interpretation | 1.0 |
| | Media consumption | 1.0 |
| | Verification of facts | 1.0 |
| | Energy statistics | 0.5 |
| | Investigations | 0.5 |
| **Creative tasks** | | **4.5** |
| | Idea generation | 1.0 |
| | Image generation | 1.0 |
| | Image management | 1.0 |
| | Brainstorming | 0.5 |
| | Content creation | 0.5 |
| | Inspiration | 0.5 |
| **Data management** | | **3.5** |
| | Coding | 1.0 |
| | Statistical basis | 1.0 |
| | Compile data | 0.5 |
| | Excel formulas | 0.5 |
| | Tweaking | 0.5 |
| **Due diligence** | | **3.5** |
| | Answer questions | 3.0 |
| | Review questions | 0.5 |
| **Research** | | **3.5** |
| | Information gathering | 1.5 |
| | Background check | 0.5 |
| | Encyclopaedia | 0.5 |
| | Environmental awareness | 0.5 |
| | Research | 0.5 |
| **Other** | | **3.0** |
| | Report writing | 1.5 |
| | Help with repetitive questions | 1.5 |
| **Legal Matters and Contracts** | | |
| **Legal & Contracts** | | **10.4** |
| | Contractual Issues | 5.0 |
| | Legal matters | 4.0 |
| | Negotiations | 1.0 |
| | Invoice management | 0.5 |
| **Business and Management** | | |
| **Facilitating tasks** | | **3.0** |
| | Proposals for new routines | 1.5 |
| | Notifications | 0.5 |

| | | |
|---|---|---|
| | Planning | 0.5 |
| | Support in work processes | 0.5 |
| **Rental** | | **2.5** |
| | Rental sketches | 1.5 |
| | Property descriptions | 0.5 |
| | Vacancy descriptions | 0.5 |
| **Business** | | **2.5** |
| | Finance | 1.0 |
| | Assess profitability in business | 0.5 |
| | Bidding | 0.5 |
| | Pitching | 0.5 |
| **Management** | | **2.0** |
| | All types of management issues | 1.0 |
| | Maintenance plans | 0.5 |
| | Technical real estate management | 0.5 |
| **Administration and Document Management** | | |
| **Administrative tasks** | | **3.5** |
| | Administrative tasks | 2.5 |
| | Create lists | 0.5 |
| | Inventory | 0.5 |
| | Layout | 0.5 |
| **Documentation** | | **3.5** |
| | Fault reports | 2.5 |
| | Protocols | 1.0 |
| **Document management** | | **3.0** |
| | Document management | 1.0 |
| | Fill in templates | 1.0 |
| | Archiving | 0.5 |
| | Structuring | 0.5 |

**Appendix 3.**

Tasks that Generative AI can largely perform on its own

| **Communication and Language Processing** | | **(%)** |
|---|---|---|
| **Text processing** | | **20.0** |
| | Drafting emails | 13.7 |
| | Formulating texts | 3.2 |
| | Summaries | 3.2 |
| **Advertising** | | **13.7** |
| | Information letters | 5.3 |
| | Advertising | 4.2 |
| | Presentations | 2.1 |
| **Communication** | | **11.6** |
| | Communication with tenants | 9.5 |
| | Communication | 2.1 |
| | FAQ | 2.1 |
| **Translation** | | **4.2** |
| | Translation | 4.2 |
| **Research and Analysis** | | |
| **Analysis** | | **7.4** |
| | Forecasts | 2.1 |
| | Consumption | 1.1 |
| | Operational optimization of properties | 1.1 |
| | Statistics | 1.1 |
| | Vacancy statistics | 1.1 |
| **Information gathering** | | **6.3** |
| | Information gathering | 6.3 |
| **Data management** | | **3.2** |
| | Calculations | 1.1 |
| | Coding | 1.1 |
| | Generate tables | 1.1 |
| **Other** | | **2.1** |

| | | |
|---|---|---|
| | Image generation | 1.1 |
| | Report Writing | 1.1 |
| **Legal Matters and Contracts** | | |
| **Legal & Contracts** | | **12.6** |
| | Lease agreements | 5.3 |
| | Invoice management | 3.2 |
| | Contracts | 2.1 |
| | Legal issues | 2.1 |
| **Administration and Document Management** | | |
| **Admin & Doc. Mgmt** | | **10.5** |
| | Fault reports | 6.3 |
| | Administrative tasks | 2.2 |
| | Digital readings | 1.1 |
| | Protocols | 1.1 |
| **Business and Management** | | |
| **Vacancy descriptions** | | **3.2** |
| | Vacancy descriptions | 3.2 |
| **Business** | | **3.2** |
| | Budget issues | 2.1 |
| | Bidding | 1.1 |
| **Other** | | **2.1** |
| | Draft maintenance plans for properties | 1.1 |
| | Planning | 1.1 |

**Appendix 4.**

Tasks that Generative AI can largely perform on its own

| **Communication** | | **(%)** |
|---|---|---|
| **Communication** | | **54.1** |
| | Customer contact | 32.3 |
| | Human interaction | 16.5 |
| | Phone contact | 1.5 |
| | Long emails | 0.8 |
| | Personal emails | 0.8 |
| | Service | 0.8 |
| | Storytelling | 0.8 |
| | Trust-building meetings | 0.8 |
| **Legal Matters and Contracts** | | |
| **Legal & Contracts** | | **18.8** |
| | Negotiations | 12.8 |
| | Agreements | 3.8 |
| | Legal tenancy issues | 1.5 |
| | Invoice management | 0.8 |
| **Business and Management** | | |
| **Management** | | **10.5** |
| | Inspections | 2.3 |
| | Leadership | 2.3 |
| | Maintenance checks | 1.5 |
| | Property solutions | 1.5 |
| | Reconstructions | 1.5 |
| | Complaints | 0.8 |
| | Site visits | 0.8 |
| **Rental** | | **6.0** |
| | Apartment/venue viewing | 5.3 |
| | Door/Entrance name changes | 0.8 |
| **Business** | | **1.5** |
| | Budget issues | 0.8 |
| | Rent levels | 0.8 |

| | | |
|---|---|---|
| **Research and Analysis** | | |
| **Research & Analysis** | | **5.3** |
| | Problem-solving | 2.3 |
| | Calculations | 1.5 |
| | Creative tasks | 1.5 |
| **Other** | | |
| **Other** | | **3.8** |
| | Assessment of people's prestige | 0.8 |
| | Evacuation in case of fire | 0.8 |
| | Fun tasks | 0.8 |
| | Responsiveness | 0.8 |
| | Updates | 0.8 |