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AI-driven Personalization in E-commerce: a Structured Literature Review

Digital Business / Information Systems Science
Bachelor's thesis

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Student’s statement regarding the use of Artificial Intelligence (AI) for preparing and/or writing this thesis:

☐ **I have not used any AI-based tools.**

☒ **I have used AI-based tools**. Their use is documented in the Appendix. The AI tools were used in a way that complies with academic integrity guidelines.

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Abstract

The rapid proliferation of e-commerce, combined with intensifying competition between digital platforms, has significantly increased the strategic importance of personalization, as businesses seek to enhance customer satisfaction, strengthen engagement, and maintain competitiveness in increasingly saturated digital markets. Simultaneously, advancements in artificial intelligence (AI), particularly in machine learning, predictive analytics and natural language processing have expanded personalization capabilities, enabling more adaptive, data-driven and individualized forms of customer interaction. Despite the prominence of AI-driven personalization in e-commerce literature, existing research predominantly focuses on the outcomes of personalization, such as customer trust and purchase behaviour, rather than on the underlying mechanisms through which personalization manifests.

This bachelor's thesis examines the central forms of AI-driven personalization identified in e-commerce literature. This thesis is guided by the following research question: What forms of AI-driven personalization are identified in e-commerce literature? The objective is to provide a conceptual framework of the most dominant AI-driven personalization mechanisms, to analyze their roles in e-commerce and to examine the influence AI has in shaping these mechanisms.

This thesis adopts a structured literature review approach based on selected peer-reviewed academic articles retrieved from the EBSCO Business Source Ultimate database. Only sources classified at levels 1-3 of the JUFO (Finnish Publication Forum) were included to ensure academic quality. Rather than constituting a fully systematic literature review, the analysis is based on a focused examination of central e-commerce studies in which AI-driven personalization is the focus of discussion. The selected literature was reviewed comparatively, and particular attention was given to mechanisms that repeatedly emerged across multiple sources, which subsequently guided the categorization and structure of the analysis.

The findings indicate that AI-driven personalization in e-commerce operates through three central and complementary forms: recommendation systems, personalized pricing and conversational agents. Recommendation systems, a central mechanism in product discovery, emerges as the most established and represented form of AI-driven personalization, while personalized pricing is characterized by its proximity to transactional decision-making and revenue optimization. Conversational agents, in turn, represent a more interaction-based form of personalization, enabling human-like communication between users and e-commerce providers. Overall, the results suggest that AI-driven technologies enable increasingly sophisticated and large-scale personalization capabilities in e-commerce, while also highlighting concerns related to transparency and implementation.

Keywords: AI-driven personalization, e-commerce, recommendation systems, personalized pricing, conversational agents, artificial intelligence, machine learning

Kandidaatintutkielma

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Abstrakti

Verkkokaupan nopea yleistyminen yhdistettynä digitaalisten alustojen välisen kilpailun kiristymiseen on lisännyt personalisaation strategista merkitystä, kun yritykset pyrkivät parantamaan asiakastyytyväisyyttä, vahvistamaan sitoutumista ja säilyttämään kilpailukykynsä yhä enemmän saturoituneessa digitaalisessa markkinaympäristössä. Samanaikaisesti tekoälyn (AI) kehitys, erityisesti koneoppimisen, ennakoivan analytiikan ja luonnollisen kielen käsittelyn osalta, on laajentanut personalisaation mahdollisuuksia mahdollistaen entistä adaptiivisempia, dataperusteisia ja yksilöllisiä asiakasvuorovaikutuksen muotoja. Huolimatta tekoälypohjaisen personalisaation näkyvyydestä verkkokauppakirjallisuudessa, tähänastinen kirjallisuus keskittyy pääasiassa personalisaation vaikutuksiin sen sijaan, että tarkastelisi niitä keskeisiä mekanismeja, joiden kautta personalisaatio toteutuu.

Tässä kandidaatintutkielmassa tarkastellaan verkkokauppakirjallisuudessa esiintyviä keskeisiä AI-pohjaisia personalisaation muotoja. Tutkimusta ohjaa seuraava tutkimuskysymys: Mitä tekoälypohjaisen personalisaation muotoja verkkokauppakirjallisuudessa tunnistetaan? Tutkielman tavoitteena on muodostaa käsitteellinen kokonaiskuva keskeisimmistä tekoälypohjaisista personalisaatiomekanismeista, analysoida niiden roolia verkkokauppaympäristössä sekä tarkastella tekoälyn vaikutusta mekanismien toimintaan.

Tutkielma perustuu jäsenneltyyn kirjallisuuskatsaukseen, joka nojaa valikoituihin vertaisarvioituihin tieteellisiin artikkeleihin. Aineisto on haettu EBSCO Business Source Ultimate -tietokannasta, ja mukaan on otettu ainoastaan JUFO (Julkaisufoorumi) -tasoille 1–3 sijoittuvat julkaisut akateemisen laadun varmentamiseksi. Tutkielma ei ole metodologisesti täysin systemaattinen kirjallisuuskatsaus, vaan se perustuu keskeisten verkkokauppatutkimusten kohdennettuun tarkasteluun, jossa tekoälypohjainen personalisaatio on tarkastelun ytimessä. Valittua kirjallisuutta tarkasteltiin vertailevasti, ja erityistä huomiota kiinnitettiin mekanismeihin, jotka toistuivat useissa lähteissä ja ohjasivat siten analyysin kategorisointia ja rakennetta.

Tulokset osoittavat, että tekoälypohjainen personalisaatio verkkokaupassa rakentuu kolmen keskeisen ja toisiaan täydentävän muodon varaan: suosittelujärjestelmät, personoitu hinnoittelu ja keskustelupohjaiset agentit. Suosittelujärjestelmät, jotka toimivat keskeisenä tuotteiden löydettävyyttä tukevana mekanismina, näyttäytyvät kirjallisuudessa vakiintuneimpana ja selkeimmin jäsenneltynä muotona, kun taas personoitu hinnoittelu korostuu läheisenä ostopäätöksentekoon ja tuottojen optimointiin liittyvänä mekanismina. Keskustelupohjaiset agentit puolestaan edustavat enemmän vuorovaikutukseen perustuvaa personalisaation muotoa mahdollistaen ihmismäisen kommunikaation käyttäjien ja verkkokauppatoimijoiden välillä. Kokonaisuutena tulokset osoittavat, että tekoälypohjaiset teknologiat mahdollistavat yhä kehittyneempiä ja laajamittaisempia personalisaatiokäytäntöjä verkkokaupassa, mutta tuovat samalla mukanaan myös läpinäkyvyyteen ja toteutukseen liittyviä haasteita.

Avainsanat: Tekoälypohjainen personalisaatio, verkkokauppa, suosittelujärjestelmät, personoitu hinnoittelu, keskusteluagentit, tekoäly, koneoppiminen

TABLE OF CONTENTS

FIGURES (begin from a new page)

No table of figures entries found.

TABLES

1 Introduction

1.1 Thesis Context and Background

The proliferation of e-commerce over recent decades has transformed digital trade from an emerging method of digital consumerism into an integral part of the global economy (Bocean et al., 2025; Mani et al., 2025). In contemporary e-commerce literature, this transformation is associated not only with technological advancement, but also with broader changes in customer behaviour, business relationships and operational strategies (Bocean et al., 2025; Mani et al., 2025). As digital markets have matured and competition has intensified, the ability to deliver relevant and differentiated customer experiences has become increasingly crucial for businesses operating in e-commerce environments (Mani et al., 2025; Teepapal, 2025; Varma et al., 2025).

Existing literature describes personalization as a dynamic, data-driven and predictive process in which real-time behavioural and contextual information is used to tailor digital content, interactions and offers to customers at scale (Mani et al., 2025; Varma et al., 2025; Vashishth et al., 2024). In this context, artificial intelligence (AI) in this thesis refers primarily to machine learning-based and adaptive data-processing technologies, such as predictive analytics, neural-network-based recommendation models and natural language processing systems utilized in conversational agents (Gao & Liu, 2022; Karthiga et al., 2025; Zhang et al., 2025). The increasing use of these technologies has further expanded personalization capabilities, enabling businesses to move from broader, more static personalization practices toward highly adaptive and individualized forms of customer interaction (Bocean et al., 2025; Mani et al., 2025).

Importantly, Gao & Liu (2022) suggest that AI-driven personalization in e-commerce encompasses a variety of distinct technological forms rather than a single, homogeneous approach. However, based on the observations of the author of this bachelor's thesis, the forms, functions and applications remain fragmented across the existing scholarship, highlighting the need for a structured examination to provide a foundation for a more integrated and well-rounded understanding.

1.2 Research Problem and Identified Research Gap

Gao & Liu (2022) emphasize that AI-driven service systems in digital environments, particularly machine learning-based recommendation, pricing and conversational systems, do not represent a uniform phenomenon but instead manifest through multiple forms, applications, and levels of intelligence. As with AI-driven personalization mechanisms, the intelligence of these services can be further categorized into different levels progressively developing from purely mechanical and automation-based towards more adaptive, interpretive and empathetic forms based on their ability to learn from data, adapt to contextual information and approximate aspects of human cognition (Gao & Liu, 2022; Huang & Rust, 2018). Importantly, according to Huang and Rust (2018), AI-driven service systems are not limited to a single functionality but often integrate multiple capabilities, which is particularly relevant in e-commerce environments where personalization mechanisms operate concurrently across the different stages of the customer journey.

Although existing e-commerce literature frequently references AI-driven personalization, it predominantly emphasizes their outcomes rather than the underlying forms and functional characteristics. For example, Mani et al. (2025) examine how AI-driven personalization features, such as responsiveness, perceived reliability and user experience influence customer trust and behaviour. Similarly, Sharma et al. (2025) focus specifically on AI-driven recommendation systems and their effects on perceived personalization, algorithmic trust and purchase intention. In addition, Varma et al. (2025) and Teepapal (2025) emphasize broader outcomes related to brand loyalty, customer engagement and consumer perceptions. While these studies acknowledge the presence of personalization mechanisms, they are primarily treated as supporting components rather than as independent objects of analysis. Consequently, the technical logic, functions and operational role of AI-driven personalization mechanisms are frequently overshadowed by downstream effects, leaving their structural composition largely implicit.

Moreover, while conceptual frameworks exist that distinguish AI systems, these perspectives are rarely applied to structurally organize and analyze the mechanisms specifically within the context of e-commerce. As a result, to the best of the author's knowledge, existing literature lacks a consolidated overview explicitly identifying the central forms of AI-driven personalization prevalent in e-commerce literature.

1.3 Research Question and Contribution

To address this gap, this bachelor's thesis examines the most central forms of AI-driven personalization identified in e-commerce literature. The aim is not to evaluate all existing applications comprehensively, but to identify the forms that recur in the selected literature and to provide an overview of how these forms as well as their key mechanisms are conceptualized, what functions they serve in e-commerce, and how AI impacts their operation.

Accordingly, this thesis is guided by the following research question:

- RQ: What forms of AI-driven personalization are identified in e-commerce literature?

By addressing this question, this bachelor's thesis contributes to a clearer understanding of AI-driven personalization in e-commerce. More specifically, it organizes the examined literature around three central forms that repeatedly emerge across the selected sources: recommendation systems, personalized pricing, and conversational agents. In doing so, this thesis shifts attention from outcome-oriented discussion toward the mechanisms themselves and provides a basis for understanding how different forms of AI-driven personalization are applied in e-commerce contexts.

1.4 Approach and Structure

This thesis adopts a structured literature review approach based on selected peer-reviewed academic sources. Rather than constituting a systematic literature review in the strict methodological sense, this thesis is based on a focused examination of e-commerce studies in which different forms of AI-driven personalization are repeatedly discussed. This analysis is therefore guided by the recurrence and relevance of these forms and the mechanisms through which they are implemented across the litearture examined.

The literature in its entirety used in this thesis was retrieved from the EBSCO Business Source Ultimate database. Only peer-reviewed academic articles classified at JUFO (Finnish Publication Forum) levels 1-3 were included. Alongside general search terms e.g., "e-commerce OR electronic commerce", "artificial intelligence OR AI", "machine learning OR ML" and "personalization" the literature search included more mechanism-specific search terms e.g., "recommendation systems", "dynamic pricing OR personalized pricing" and "chatbot OR conversational agent". These criteria were used to ensure both academic quality and topical relevance.

During the review process, the selected sources were compared with particular attention given to recurring forms and mechanisms related to AI-driven personalization. Similarities and differences between the sources were identified, organized and grouped together to support the structure of the analysis. Rather than examining the studies as isolated cases, the review process focused on identifying broader themes, recurring patterns and conceptual similarities.

This thesis is structured as follows: Chapter 2 examines the central forms of AI-driven personalization identified in the selected literature. In the subsections of Chapter 2, the main form is first introduced through a general overview, after which the more specific mechanisms and applications are discussed in greater detail. Finally, Chapter 3 presents the overall conclusions of the thesis.

To structure the analysis, a subset of key sources was identified from the selected literature. These "anchor sources" represent studies in which AI-driven personalization is discussed more broadly across multiple mechanisms, and were selected based on their relevance, scope and contextual suitability. The following anchor sources were used as the primary basis for identifying the central forms of AI-driven personalization examined in this thesis:

Anchor source	Research context	Method / Approach	Conclusions
(Varma et al., 2025)	AI-driven personalization strategies and brand loyalty in digital marketplaces	Mixed-method study combining data analysis, machine-learning simulations and consumer surveys	Suggests that AI-driven personalization strengthens perceived relevance and consumer trust. Highlights how machine learning-based personalization can improve customer relationships and loyalty.
(Teepapal, 2025)	AI-driven personalization in social media and digital marketing	Quantitative survey-based study	Suggests that AI-driven personalization positively influences customer engagement and trust, improving customer interaction.
(Huang & Rust, 2018)	AI and human-machine interaction in service environments	Conceptual and theoretical study	Categorizes AI intelligence into four separate forms: mechanical, analytical, intuitive and empathetic. Suggests that AI in service systems progressively replaces and/or augments service tasks.
(Gao & Liu, 2022)	AI-driven personalization throughout the customer journey in interactive marketing	Literature review and existing customer journey framework analysis	Suggests that AI-driven personalization manifests through multiple forms across the customer journey including profiling, navigation and retention, and emphasizes the role of AI in improving customer interaction.
(Vashishth et al., 2024)	AI-driven content personalization in e-commerce marketing and customer experience	Literature review, case study examination and empirical company evidence examination	Suggests that AI-driven personalization especially through recommendation systems and adaptive personalization improve customer satisfaction, engagement and conversion rates.
(Mani et al., 2025)	AI-driven personalization, customer trust and online buying behaviour in e-commerce	Quantitative study combining statistical modelling and survey data	Suggests that AI-driven personalization strengthens trust, improves user experiences and customer purchase intention.
(Bocean et al., 2025)	AI technologies in European e-commerce market development	Empirical study using Eurostat data and multivariable data-analysis methods	Suggests that AI acts as a key driver of digital transformation and customer interaction improvement; often through varying AI-driven personalization mechanisms.

Table 1. Overview of anchor sources

2 Forms of AI-Driven Personalization in E-Commerce

This chapter addresses the RQ by examining the central forms of AI-driven personalization identified in the selected e-commerce literature. As outlined in Chapter 1, the aim of this thesis is not to provide an exhaustive classification of all existing personalization mechanisms, but rather to identify and analyze those most consistently represented. The analysis therefore focuses on mechanisms that are repeatedly discussed in the literature, indicating their relevance within e-commerce environments.

Based on a review of the selected studies, three main forms of AI-driven personalization were identified through the recurring discussion and application of specific personalization mechanisms:

1. Recommendation systems
2. Personalized pricing
3. Conversational agents

Anchor source	Recommendation systems	Personalized pricing	Conversational agents
(Varma et al., 2025)	✓	✓	
(Teepapal, 2025)			✓
(Huang & Rust, 2018)	✓		✓
(Gao & Liu, 2022)	✓	✓	✓
(Vashishth et al., 2024)	✓	✓	✓
(Mani et al., 2025)	✓	✓	✓
(Bocean et al., 2025)	✓	✓	✓

Table 2. Recurring forms of AI-driven personalization in anchor sources

Additional sources focusing on specific mechanisms were subsequently used to further elaborate the functionality and deepen the analysis within each identified form.

As illustrated in Table 2, recommendation systems, personalized pricing and conversational agents appear consistently across the selected anchor sources. Several studies, such as Gao and Liu (2022), Mani et al. (2025) and Bocean et al. (2025) discuss multiple forms simultaneously, suggesting that

AI-driven personalization in e-commerce is commonly implemented through a combination of complementary mechanisms operating in parallel.

Following this overview, each form is examined individually. In each section, the form is first introduced at a general level, after which its more specific mechanisms, applications and AI-enabled characteristics are discussed in greater detail. This structure enables a comparison of the roles, technological foundations and conceptual distinctions between the different forms of AI-driven personalization.

2.1 Recommendation Systems

2.1.1 Introduction and Overview

Recommendation systems are widely described in the examined literature as one of the most prominent forms of AI-driven personalization. While Sharma et al. (2025) emphasize the role they have in influencing customer decision-making by generating personalized product suggestions based on behavioural data, Machidon (2025) highlights a broader platform-wide function. According to Machidon (2025), recommendation systems not only act as supporting mechanisms in e-commerce functions (e.g., product discovery) but play a key infrastructural role in the management and curation of the often-overwhelming volume of digital content that today's e-commerce platforms are required to process to maintain competitiveness. These differences illustrate how recommendation systems act both as customer-facing personalization tools and essential foundational components within e-commerce environments.

From a technological standpoint, recommendation systems have evolved significantly over recent years. Early models relied primarily on collaborative filtering approaches, while certain recent AI-driven recommendation systems can integrate deep neural networks, graph-based learning frameworks and leverage pre-trained large language models (LLMs) to enhance personalization accuracy and both capture and process user needs and preferences more effectively (Li, 2024; Zhang et al., 2025). However, Zhang et al. (2025) argue that despite rapid technological iteration, classical models still find widespread implementation in e-commerce environments, often combined with newer AI-based mechanisms in hybrid models tailored to specific business applications.

While Zhang et al. (2025) emphasize the importance of neural-network-based architecture development in improving recommendation accuracy, Li (2024) similarly highlights the role of richer product representation. According to Li (2024), integrating multidimensional product information such as product images, categories, and key attributes can further enhance recommendation effectiveness. Liao & Sundar (2022) argue that recommendation accuracy is by far the most important criterion for assessing the quality of the system.

2.1.2 Collaborative filtering

Collaborative filtering (CF) represents one of the most popular methods of recommendation system-based personalization in e-commerce (Lee et al., 2007; Li et al., 2026; Wang, 2023; Zhang et al., 2025). In earlier research, Lee et al. (2007) describe CF as a popular, widely adopted recommendation mechanism in e-commerce, emphasizing its role in the generation of personalized product suggestions based on user preference data. More recent studies by Li et al. (2026), Wang (2023), Zhang et al. (2025) indicate how the prominence and popularity of CF-based recommendation systems within e-commerce have remained significant to this day. For instance, Wang (2023) and Zhang et al. (2025) note how CF-based systems are widely applied across large e-commerce platforms such as eBay and Amazon.

Collaborative filtering operates by analyzing historical user-item interaction data, such as purchase histories, preference ratings, or browsing behaviour to identify similarities between users or items and generate recommendations based on shared preference patterns (Lee et al., 2007; Wang, 2023; Zhang et al., 2025). Liao & Sundar (2022) claim that these shared preferences leverage the power of large groups of similar users and can even persuade users into "bandwagon behaviour" (the notion that "if others think it's good, I should think so too"). According to Wang (2023), this operates on the assumption that users who have demonstrated similar preferences in the past are likely to exhibit these preferences in the future, thereby allowing CF-based systems to accurately predict future interests.

Despite its widespread use in e-commerce, the literature consistently highlights limitations associated with traditional CF approaches. Perhaps the most discussed challenge concerns data sparsity, which often occurs when large e-commerce platforms contain vast amounts of user and product data, but relatively limited individual user-item interaction data. Under such circumstances, CF-based systems can face reduced recommendation accuracy and unreliability (Lee et al., 2007; Wang, 2023; Zhang et al., 2025). As a result, CF-based models are likely to struggle in environments with limited historical data or a large volume of new users, a problem Li et al. (2026) refer to as the cold-start problem.

The limitations are addressed through the integration of AI and machine learning. For example, Zhang et al. (2025) describe AI-based neural CF models, where multilayer neural networks are used to capture complex non-linear relationships between users and items. Such architectures can improve recommendation accuracy, particularly in e-commerce environments, where interaction data is sparse and user-item relationships contain significant gaps (Lee et al., 2007; Wang, 2023; Zhang et al., 2025).

2.1.3 Content-based filtering

Wang (2023) describes an alternative recommendation method, content-based filtering (CBF) as one of the main recommendation methods alongside collaborative filtering. Instead of deriving patterns and grouping users based on previous interests and behaviour, CBF relies on analyzing the attributes and characteristics of individual items to generate personalized suggestions (Li et al., 2026). In this approach, recommendations are typically based on previously identified user preferences, such as preferred product categories, features, or attributes which are then matched with similar items in the system (Ye et al., 2019).

Compared to CF, CBF emphasizes a more individualized and attribute-driven recommendation logic. According to Liao & Sundar (2022), this logic is more consistent with systematic, heavily data-based information processing. Liao & Sundar (2022) contrast the differences in the two approaches by suggesting that while CF is more reliant on heuristic processing, such as collective social signals, content-based recommendations are generated through systematically evaluating product characteristics. This distinction highlights a fundamental conceptual difference between the two approaches, where CBF focuses on item-user matching, and CF emphasizes user-user similarity.

The effectiveness of CBF is highly dependent on the availability and quality of identifiable user preferences and product attributes (Liao & Sundar, 2022). Ye et al. (2019) note that CBF typically performs well when user preferences can be clearly defined and matched with product features. However, according to Ye et al. (2019), situations where preferences are difficult to systemically define or articulate, CBF can face major constraints. Similarly, Liao & Sundar (2022) highlight that CBF is often most suitable when product attributes are easily observable, comparable (e.g., electronics, furniture) and less ambiguous and experience-based (e.g., travel, food).

Together, CF and CBF are often examined in relation to one another rather than as entirely independent. For example, Wang (2023) and Zhang et al. (2025) more broadly identify both methods as core recommendation techniques, while Liao & Sundar (2022) and Ye et al. (2019) more explicitly distinguish the differences between attribute-based and socially driven recommendation processes. These findings suggest that although both approaches appear at the forefront of AI-driven personalization in e-commerce literature, and are often observed in parallel, they differ in the underlying mechanisms, data dependencies and contextual suitability.

2.1.4 Hybrid models

In addition to CF and CBF, the literature examined consistently mentions a third principal category of recommendation systems, namely hybrid models (Gao et al., 2021; Li et al., 2026; Qiu et al., 2022; Ye et al., 2019). In these models, recommendation mechanisms from individual systems, primarily CF and CBF, are combined into a merged model to overcome previous limitations, improve recommendation accuracy, and allow the system to be tailored more effectively to specific business needs (Li et al., 2026; Ye et al., 2019). Another key motivation for this integration is the need to address commonly identified challenges, such as data sparsity and the cold-start problem, which are frequently associated with CF- and CBF-based approaches (Gao et al., 2021; Li et al., 2026; Qiu et al., 2022; Ye et al., 2019).

Beyond this general principle, the literature presents AI-driven approaches for implementing hybrid models in practice. For example, Qiu et al. (2022) propose a deep learning-based hybrid model which utilizes natural language processing to integrate multiple sources of information, including user ratings, review data, and item content descriptions. Testing the model against large-scale Amazon product datasets, Qiu et al. (2022) demonstrate how the integration of heterogeneous data sources can significantly improve recommendation accuracy, particularly in large-scale e-commerce environments. Similarly, Ye et al. (2019) present a machine learning-based hybrid recommendation model that achieves significantly higher accuracy compared to its two benchmark systems (CF and CBF). Together, these proposed models illustrate how AI enables hybrid models to extend beyond simple method combination by facilitating more efficient integration and utilization of diverse data sources.

Importantly, it is suggested that hybrid models are not developed independently but instead build directly on earlier CF and CBF approaches. For instance, Ye et al. (2019) explicitly treat CF and CBF as benchmark methods against which hybrid models are developed and evaluated. Similarly, Li et al. (2026) describe hybrid models as approaches that combine the strengths of both CF and CBF, indicating that hybrid models can be understood as a continuation of these two foundational approaches rather than as entirely separate systems.

2.2 Personalized Pricing

2.2.1 Introduction and Overview

Price-based personalization is described in e-commerce literature as a central, pricing-focused dimension of AI-driven personalization (Gao & Liu, 2022; Hufnagel et al., 2022; Karthiga et al., 2025). Gao & Liu (2022) conceptualize personalized pricing as a mechanism aimed to facilitate purchasing by first accurately identifying a customer’s willingness to pay and adjusting pricing accordingly to maximize profit. Similarly, Karthiga et al. (2025) emphasize how especially today’s AI- and data-driven, increasingly flexible pricing mechanisms can offer significant competitive advantages in an e-commerce environment.

In contrast to recommendation systems, the primary function of price-based personalization is to directly influence transaction outcomes by shaping the purchasing conditions, specifically by adapting the price (Gao & Liu, 2022). While recommendation systems guide product discovery and customer decision making (Sharma et al., 2025), pricing mechanisms operate closer to the point of purchase, representing a more immediate and outcome-oriented form of personalization within a customer’s purchasing journey (Gao & Liu, 2022).

The development of price-based personalization has evolved alongside the advancements in AI, data availability and utilization (Karthiga et al., 2025). While earlier forms of price personalization were often based on relatively simple and broad contextual variables, such as location or date, more recent models incorporate AI and machine learning, thus being able to process larger and more complex datasets in pricing decisions (Gao & Liu, 2022; Karthiga et al., 2025). As noted by Hufnagel et al. (2022), improvements in customer profiling, data collection, and data processing have contributed significantly to the shift in pricing strategies from broadly applied to highly individualized.

However, the literature raises certain concerns alongside the evolving sophistication of AI-driven pricing mechanisms. For instance, Gao & Liu (2022) note how hyperpersonalized pricing may face challenges related to transparency and potential exploitation of both the pricing mechanism and the customer.

2.2.2 Dynamic Pricing

To the best of the author’s knowledge, dynamic pricing is described in the examined literature as perhaps the most prominent form of price-based personalization in e-commerce, used interchangeably with personalized pricing (Gao & Liu, 2022; Varma et al., 2025; Vashishth et al., 2024). Dynamic pricing refers to a pricing model where prices are adjusted in response to changing market conditions, user behaviour and a variety of contextual factors (Karthiga et al., 2025). Contrasting it with static models, Karthiga et al. (2025) describe how dynamic pricing models enable businesses in e-commerce to better respond to fluctuations in demand, competition and changing customer behaviour consequently improving revenue optimization and competitiveness.

Following technological advancements in the e-commerce space, dynamic pricing is increasingly enabled by AI and machine learning approaches, allowing pricing mechanisms to process larger volumes of data, learn and adapt from past transactions and optimize pricing in real time (Gao & Liu, 2022; Karthiga et al., 2025). For example, Karthiga et al. (2025) propose that AI-driven pricing systems utilize predictive analytics to forecast demand, segment and group customers, and determine optimal pricing strategies based on historical data, browsing behaviour and external factors such as seasonal or market trends. Karthiga et al. (2025) claim that these systems rely on deep learning and neural networks to identify complex patterns and continuously refine and optimize pricing decisions.

Hufnagel et al. (2022) argue that the level of personalization in dynamic pricing models varies, ranging from simpler, less personalized mechanisms based on time, location, competitor or supply/demand conditions to individually tailored customer-based pricing. Hufnagel et al. (2022) also propose that while earlier, less personalized forms of dynamic pricing have long been applied in e-commerce, more precise and highly personalized pricing mechanisms have emerged more recently alongside improvements in data availability and AI capabilities. This would suggest that AI-driven dynamic pricing models have evolved from broadly applied, context-based price adjustments toward increasingly intricate, individualized and data-driven pricing mechanisms.

However, personalization in pricing is not limited explicitly to customer-level profiling. As Hufnagel et al. (2022) indicate, dynamic pricing may result in price differences within individual customers even with the absence of highly individualized data because of broader contextual variables and factors. This implies that pricing differences at the individual level may arise not only from precise customer profiling, but also from context-driven mechanisms, highlighting a more nuanced and indirect form of personalization within dynamic pricing.

2.2.3 Personalized Promotions

Personalized promotions and offers represent a complementary form of AI-driven price personalization in e-commerce (Gao & Liu, 2022; Hufnagel et al., 2022; Karthiga et al., 2025; Vashishth et al., 2024). Described as data-driven and predictive approaches that deliver targeted incentives based on customer behaviour and contextual signals, Gao & Liu (2022) emphasize how such data-driven systems allow e-commerce companies to anticipate customer needs and deliver tailored promotional offers in real time, and propose that as a result promotional offers can be presented at moments when the customer is most likely to make a purchase.

To the best of the author's knowledge, personalized promotions and offers are rarely treated as a fully distinct mechanism in e-commerce literature, instead often discussed in close connection with dynamic pricing models. For example, Karthiga et al. (2025) discuss personalized promotions and discounts as central variable factors in predictive dynamic pricing models, and Hufnagel et al. (2022) only briefly mentions personalized offers while discussing dynamic pricing. In addition, Gao & Liu (2022) discuss personalized promotion primarily in the context of broader "personalized nudging" mechanisms aimed to facilitate purchase decisions within customers.

Therefore, the literature examined would indicate that personalized promotions and offers are predominantly conceptualized in conjunction with broader pricing strategies rather than as independent personalization mechanisms. Consequently, their role appears to be closely integrated within dynamic pricing, particularly in AI-enabled systems where price optimization is based on highly individualized real-time data and predictive analytics (Hufnagel et al., 2022; Karthiga et al., 2025).

2.3 Conversational Agents

2.3.1 Introduction and Overview

Conversational agents are described in e-commerce literature as an increasingly prominent form of AI-driven personalization, enabling human-like interaction between customers and digital platforms. While Huang & Rust (2018) conceptualize conversational agents as "empathetic" forms of AI capable of learning, adapting and mimicking aspects of human conversation, Gao & Liu (2022) emphasize their role in e-commerce as promising tools designed to enhance customer interaction. Similarly, Khandelwal et al. (2025) highlight how AI-driven conversational agents have become essential in e-commerce for improving customer support, streamlining purchasing processes and influencing customer behaviour.

Within e-commerce environments, conversational agents primarily function as interactive, front-end interfaces that facilitate continuous communication between customers and businesses (Bocean et al., 2025; Lim et al., 2022). According to Bocean et al. (2025), Pham et al. (2025) and Khandelwal et al. (2025), conversational agents are widely adopted in customer service and support contexts, where they provide the benefits of instant responses, 24/7 availability and significant reductions in operational and human workloads. Beyond reactive support, conversational agents can proactively guide customers through purchase processes, provide recommendations and enhance decision-making processes through highly personalized assistive interactions (Lim et al., 2022; Pham et al., 2025).

Conversational agents are enabled by advances in AI, particularly by natural language processing and machine learning, which allow these systems to interpret, generate, learn from, and adapt to communication based on customer input (Bocean et al., 2025; Lim et al., 2022, Khandelwal et al., 2025). Huang & Rust (2018) propose that conversational agents represent higher-level AI capabilities due to their ability to incorporate adaptive learning with elements of human-like interaction. Recent developments, such as voice-based AI agents have further extended these capabilities, embedding human-AI conversations seamlessly into everyday contexts (Sun et al., 2025). Particularly in e-commerce, Khandelwal et al. (2025) highlight the rapid growth and increasing adoption of conversational agents in businesses, driven by the potential to enhance operational efficiency, and enable more data-driven personalization services.

2.3.2 Indistinct Forms

The literature examined discusses the term “chatbot” interchangeably with conversational AI or conversational agents (Gao & Liu, 2022; Pham et al., 2025; Khandelwal et al., 2025). However, it is important to note that such terminology may oversimplify the phenomenon.

Conversational agents manifest in multiple forms depending on the service context, personalization requirements and technological environment in which they operate (Lim et al., 2022; Sun et al., 2025). For example, conversational agents may appear in text-based customer service chatbots, voice-based assistants such as Amazon’s Alexa or Apple’s Siri, or more complex systems incorporating visual, embodied, or multimodal interaction (Gao & Liu, 2022; Lim et al., 2022; Sun et al., 2025). Lim et al. (2022) further propose that conversational agents can take on multiple functional roles in e-commerce, acting not only as service assistants but as recommendation agents or even social companions used to replicate aspects of social interaction typically absent in online shopping environments.

Despite these variations, the underlying logic of conversational agents remains relatively consistent across different forms. As suggested by Huang & Rust (2018) and Lim et al. (2022), conversational agents are fundamentally designed to simulate human-like conversation and interaction, enabling high levels of personalized engagement between users and digital platforms.

However, compared to more clearly defined mechanisms such as recommendation systems, conversational agents appear conceptually more difficult to categorize and articulate within the literature. As noted, terms such as "chatbot" can create a sense of ambiguity when used interchangeably with broader concepts such as conversational agents. This ambiguity may however reflect the relatively recent and rapidly evolving nature of contemporary research regarding conversational AI, where conceptual boundaries remain less established in the literature.

At the same time, the literature identifies challenges related to conversational agents. Khandelwal et al. (2025) highlight issues concerning data quality and integration requirements, technical limitations and data security. Khandelwal et al. (2025) also describe the importance of aligning conversational agents with brand identity and maintaining the human-like interaction quality often expected by customers.

3 Discussion & Conclusions

The analysis presented in this bachelor's thesis suggests that AI-driven personalization is not a uniform phenomenon but rather consists of multiple distinct forms and mechanisms that differ significantly in functionality, technological requirements, and conceptual clarity. Based on the literature examined in this thesis, recommendation systems, price-based personalization and conversational agents emerge as the three central forms through which AI-driven personalization is implemented in e-commerce environments.

Recommendation systems are consistently described as the most established and clearly defined form of AI-driven personalization, focusing primarily on product discovery and customer decision facilitation through data-driven suggestions (Sharma et al., 2025; Zhang et al., 2025). The literature surrounding recommendation systems establishes a relatively clear conceptual structure within this form of personalization. This is due to the clear distinction between collaborative filtering, content-based filtering and hybrid models, all of which are extensively compared, described and applied through practical examples (e.g., Liao & Sundar, 2022; Wang, 2023; Ye et al., 2019). This indicates that recommendation systems represent a relatively mature area of research, characterized by well-defined mechanisms.

In contrast, personalized pricing operates closer to the point of transaction, directly influencing purchasing processes by adapting pricing decisions based on customer behaviour and a variety of contextual factors (Gao & Liu, 2022). Within this form, dynamic pricing, often used interchangeably, emerges as the dominant mechanism, supported by AI-driven predictive analytics and real-time data processing (Karthiga et al., 2025). Compared to recommendation systems, price-based personalization appears more strategically oriented toward direct revenue optimization and competitive positioning, while raising concerns related to transparency and exploitation (Gao & Liu, 2022; Hufnagel et al., 2022).

Conversational agents, in turn, represent an interaction-based form of personalization, enabling continuous and human-like interaction between users and digital providers (Huang & Rust, 2018; Lim et al., 2022). While their role in enhancing customer engagement and operational efficiency is widely acknowledged (Bocean et al., 2025; Pham et al., 2025; Khandelwal et al., 2025), the literature suggests that conversational agents are less distinctively defined compared to other personalization mechanisms. Terms such as "chatbot" are used in the literature interchangeably with broader concepts of conversational AI, despite the presence of multiple distinct forms and implementations (Gao &

Liu, 2022; Pham et al., 2025). Importantly, although manifested in multiple forms, such as text-based chatbots, voice assistants, and advanced multimodal systems, these variations are primarily driven by differences in channels, environments and capabilities rather than fundamentally distinct personalization mechanisms (Huang & Rust, 2018; Lim et al., 2022; Sun et al., 2025).

Altogether, these findings highlight that AI-driven personalization in e-commerce operates through multiple complementary mechanisms, each fulfilling a distinct role within the customer's journey and business strategy. While recommendation systems focus on guiding decision making and product suggestions, personalized pricing systems directly shape transaction conditions, and conversational agents facilitate interaction. The increasing integration of machine learning-based analytics, predictive systems and natural language processing technologies across these mechanisms enables increasingly sophisticated and scalable personalization capabilities for businesses operating in e-commerce environments.

Additionally, the findings of this thesis suggest that AI-driven personalization in e-commerce is evolving toward increasingly integrated and interaction-oriented forms that often operate simultaneously throughout the customer journey. This highlights the growing complexity of personalization practices in e-commerce environments and demonstrates how AI-driven personalization is increasingly developing from isolated recommendation or interaction mechanisms toward broader personalization ecosystems embedded across digital commerce platforms. Rather than functioning as separate technological tools, personalization mechanisms increasingly support multiple simultaneous purposes related to customer interaction, decision facilitation and operational efficiency throughout e-commerce environments.

However, this thesis is subject to certain limitations. As the study is based on a structured literature review rather than empirical analysis, the findings depend on the scope, selection and interpretation of the literature examined. In addition, both AI technologies and e-commerce environments are developing rapidly, while the academic literature surrounding AI-driven personalization remains relatively recent and still evolving. Consequently, the conceptualization, implementation and practical applications of AI-driven personalization mechanisms may change significantly as technologies and research continue to develop. Emerging forms of AI-driven personalization, such as generative AI applications and advanced multimodal conversational systems, remain comparatively less represented in the current academic literature and could therefore be examined in greater detail in future research. Furthermore, future studies could investigate how different personalization forms interact and evolve within practical e-commerce environments over time.

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Explanation of the use of AI

In the creation of this thesis, I utilized generative AI for several supporting tasks. The tools used, their purpose and the verification measures are detailed below. I confirm that I have used AI tools with appropriate care and caution, have fully disclosed their use in accordance with university policy, and take full responsibility for all content presented in this thesis.

1. Tool: OpenAI's ChatGPT (GPT-5.3 version)

Stage of use: Thesis topic ideation, narrowing scope of topic and refinement of research questions

Purpose of use: I used ChatGPT at the early stages to brainstorm possible thesis topics based on my pre-existing interests. Initially, I was interested in the use of AI within sales or customer service, and conversing with ChatGPT helped to narrow down a broader area of interest into a more specific, feasible topic, and to formulate and refine research questions.

- **Example prompt:** *"I want to explore your suggested AI-driven personalization topic more. As I'm writing a bachelor's thesis, the topic needs to be sufficiently narrow but have enough academic literature to base a literature review on. It also needs to be examined through concise research questions. Give me some examples of frameworks around AI-personalization, that are not too broad and might be a good basis for a bachelor's thesis."*

Verification: The outputs were used only as a starting point for ideation and scoping. Initially, ChatGPT suggested multiple topics such as *"Impact of AI Chatbots on Customer Service Efficiency and Experience in Digital Business"* and *"Generative AI in Sales Enablement: Effect on Sales Process and Customer Engagement",* which helped me narrow down and refine the scope of the thesis. The final thesis, scope, and research questions were determined by me based on my own judgement and went through months of iteration and refinement. No AI-generated suggestions were taken directly or uncritically.

Stage of use: Chapter structure and paragraph organization

Purpose of use: I used ChatGPT to structure sections and subsections to ensure logical progression in the thesis. By discussing chapter divisions, subsection logic and the order in which concepts should be presented, ChatGPT helped me organize different sections into coherent thematic categories.

- **Example prompts:** *"How could I structure a subsection so that it first introduces the mechanism generally and moves to specific forms and examples in an academically coherent way?"* **or** "*Should this X part from subsection Y instead be moved after subsection Z to ensure logical progression?"*

Verification: The proposed structures were treated as organizational suggestions to ensure logical flow in the thesis. As these are merely suggestions, the final content, ordering of sections and analytical emphasis are my own.

Stage of use: Language support, grammar checking, and rephrasing

Purpose of use: I used ChatGPT as a language-support tool to improve clarity, grammar, flow and academic style, as English isn't my native language.

- **Example prompts:** *"Without changing any of the contents, please check this paragraph to ensure proper grammar and academic tone"* **or "***Give me suggestions on how to rephrase this sentence to ensure proper flow in the paragraph."*

Verification: Had I not checked the grammar with ChatGPT, all my *"competitive"* words would've been spelled *"competetive"*. In addition, an example of rephrasing would be what's currently written as *"...this transformation is associated not only with technological advancement..."* was originally *"... this rapid evolution process is credited to more than advancements in technology..."* ChatGPT was only used for linguistic support, not for generating independent academic claims.

Stage of use: Quality assurance and critical reflection to maintain analytical scope of thesis

Purpose of use: I used ChatGPT as a means of critical reflection on whether certain parts of the text appeared too repetitive, unclear or broad. I used it to help assess whether individual sections aligned with the framework of the thesis. This helped me identify if example further clarification or adjustment was required.

- **Example prompt:** *"Does this section remain within the scope of my research question, or does it drift too far beyond the focus of the thesis?"*

Verification: I used these outputs only as a "second opinions" based on my own thoughts, doubts or ideas and as general feedback to continuously reiterate and reevaluate what I had written. All conclusions and interpretations in the final thesis are my own.