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Project Title: Technology Transfer of AI-based Recommendation System from E-Commerce Market to Sustainable Consumption Market

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Summary

Artificial Intelligence (AI) is gaining popularity across various markets, and consequently, the transfer of AI technology presents significant opportunities. This research project delves into the promising area of technology transfer, focusing on the transition of AI-based recommendation systems from the established e-commerce market to the emerging market of sustainable consumption. This transfer not only opens up a new market opportunity for sustainable consumption but also tackles prevalent challenges, including gaps in awareness, engagement, information overload, behavior change, and personalization. The increasing desire to lead sustainable lives is driving the growth of the sustainable consumption market, pointing towards significant prospects. While recommendation systems have demonstrated substantial impacts in different markets, their potential shines particularly in the e-commerce market. Bridging the gap between e-commerce and sustainable consumption reveals a realm of market potential, empowering consumers to make ethical and environmentally conscious choices.

The research methodology relies on secondary data collection and aims to explore the potential of transferring recommendation system technology to the sustainable consumption market. The implementation of the recommendation system can be strategically directed towards waste management recommendations, sustainable product recommendations, and energy consumption recommendations. The data analysis indicates a positive acceptance of recommendation system technology in various markets, suggesting a favorable probability of its adoption in the sustainable consumption market as well. Furthermore, the influence of product recommendations on product views and purchase activities is evident. In the context of the emerging sustainable consumption market, this influence holds the promise of attracting more consumers and expanding future potential. The data analysis also sheds light on public perceptions of waste management and energy consumption practices, providing additional support for the transfer of recommendation systems to sustainable consumption. However, amidst the promising aspects of the recommendation system, challenges arise in the technology transfer process. These encompass data privacy and trust concerns, complex sustainability criteria, limited data availability, and diverse consumer preferences in relation to sustainability. The business potential of this study is profound. By bridging the proven success of e-commerce with the nascent sustainable consumption market, recommendation systems have the capacity to reshape consumer decision-making paradigms. In a rapidly evolving landscape, the technology transfer from e-commerce to sustainable consumption is a dynamic endeavor. It holds the potential to address market gaps, drive shifts in consumer behavior, and foster a culture of environmental responsibility.

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1. Introduction

In an era of novel technological advancement, Artificial Intelligence (AI) stands as a resounding testament to human innovation. This transformative force has influenced virtually every aspect of modern life, revolutionizing markets, redefining opportunities, and reestablishing the limits of invention (Montreal AI Ethics Institute, 2022). The magnitude of global expenditures reflects the expanding interest in AI's potential to transform economies. According to forecasts by the International Data Corporation (IDC), the worldwide investment in AI is anticipated to nearly reach $98 billion in 2023, which is more than twice the $37.5 billion spent in 2019 (Collins et al., 2021).

As people have become accustomed to automation and a diminished human presence in various spheres of society, the emergence of the COVID pandemic has heightened their fascination with AI (Coombs, 2020). It has been a rapidly evolving technological trend that every market is attempting to capitalize on for increased efficiency and lower costs (Hossein et al., 2020). In today's changing global economy, businesses are constantly on the lookout for new methods to sustain their innovation and competitive edge. In such circumstances, the incorporation of AI into organizational and information technology (IT) strategies emerges as a promising path to prospective benefits (Perifanis and Kitsios, 2023). This is evident in the cases of Airbnb and Uber, which have enthusiastically adopted AI to create innovative business models. (Lee et al., 2019) These instances demonstrate that AI stands out as one of the most noteworthy technological leaps and has played a transformative role in reshaping markets.

The expansion of AI's influence is not limited to specific pockets of industry; rather, it has permeated diverse markets, ushering in a new era of opportunities (United Nations, 2021). As AI continues to drive innovation and progress within specific markets, a new frontier emerges: the transfer of AI technology between markets. This idea of technology transfer refers to the movement of AI potential, expertise and applications from one market to another. This dynamic process has the potential to fill gaps, foster collaboration, and strengthen the transformative potential of AI beyond the limits of specific markets. Recent statistics from Tractica indicate that the market for AI-based technologies grew by $1.4 billion in 2016 and is projected to reach $59.8 billion by 2025 (Capterra, 2020). This clearly demonstrates the potential of transferring AI technology across various markets.

In addition, the practice of technology transfer itself offers numerous benefits. Over the past four decades, technology transfer has fostered innovations, contributed more than $1.3 trillion to economic growth in the United States, and supported an estimated 11.2 million jobs. Multiple nations have recognized this growing trend, prompting them to follow a similar path (IAM, 2022). Through the transfer of AI between markets, businesses can reduce expenditures on research and development, accelerate project timelines, and gain a competitive edge. AI has shown the potential to transform industries and sectors ranging from supply chain management to medicine (Chi et al., 2020). New information and technologies do not develop everywhere at once. Thus, the significance of technology transfer between markets has grown (Aslam et al., 2018).

This research aims to explore the **potential of technology transfer of AI** between markets. The act of transferring AI technology enables markets to utilize accumulated knowledge, research, and advancements rather than beginning from scratch. This undertaking holds significant promise within the market, and among the most groundbreaking facets of AI is the **Recommendation System** (Zhang et al., 2019). This research intends to examine the AI-based Recommendation system as a representative transfer case, transitioning it from established domains such as e-commerce to a growing sustainable consumption market. The focus will be on analyzing how it can be used effectively in the new market, examining challenges, and identifying the key factors that influence the success of transferring AI technology.

2. Problem Domain

Growing markets, particularly those such as the sustainable consumption sector, frequently face a number of distinct issues that can impede their development and impact. These hurdles such as the lack of personalization, limited engagement, resistance to behavior change, limited consumer awareness, and information overload paint a complex landscape that necessitates innovative solutions to foster expansion. The following concerns constitute the problem domain.

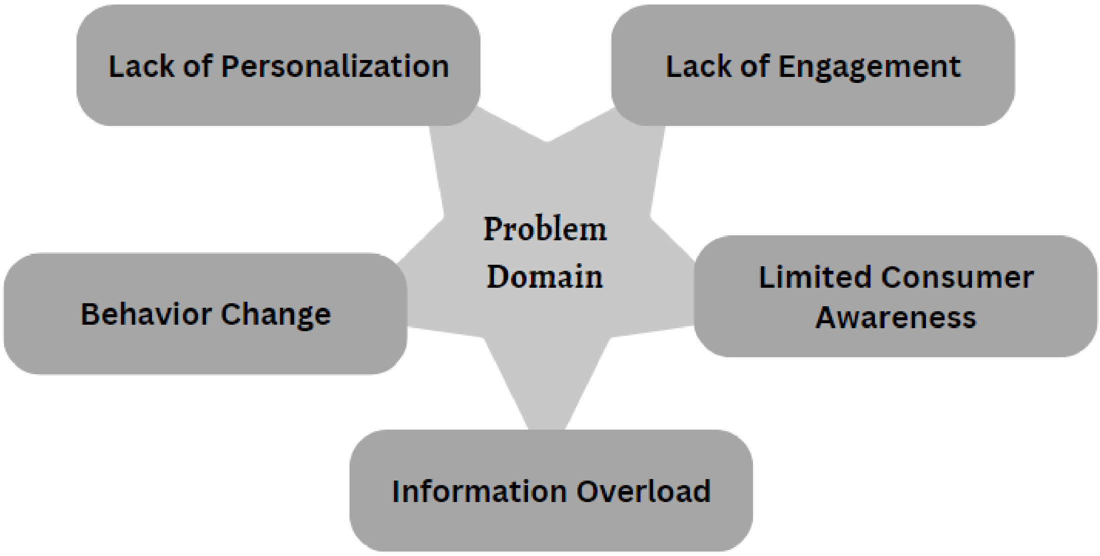

Figure 1: Problem Domain

- **Lack of Personalization:**
  In a number of emerging markets, individuals frequently encounter generalized approaches that do not cater to their particular needs and preferences. In the absence of personalized experiences, there may be a disconnection between consumers and the offered products or services. Without customized recommendations, consumers may have difficulty locating options that align with their values and preferences, resulting in a lower likelihood of product purchase. Personalization aids in meeting consumer needs, thus positively influencing the likelihood of repeat purchases (Arora et al., 2021). Employing user profiles, previous interactions, and explicit feedback to comprehend user preferences not only reduces expenses associated with customer searches and product evaluation but also heightens customer loyalty. As a result, this becomes mutually advantageous for both retailers and consumers (Tyrväinen et al., 2020).

- **Lack of Engagement:**
  Emerging markets face a challenge in retaining the attention of consumers and keeping them engaged with new market offerings. The inability of conventional methods of communication to captivate audiences may result in a lack of sustained interest. This disengagement may hinder the market's capacity to raise awareness and encourage active participation. Research indicates that customer engagement, a key driver of business growth, is significantly influenced by word-of-mouth recommendations (Roy et al., 2020). Moreover, in the retail industry, positive word-of-mouth endorsements can have a greater impact than repeat purchase behavior (Van Doorn et al., 2010). An effective approach to enhancing customer engagement involves recommending products and services endorsed by similar users with positive ratings.

- **Behavior Change:**
  Encouraging behavioral changes is a formidable challenge across all market landscapes, particularly in emerging markets such as the sustainable consumption market, where established practices may resist change (Jackson, 2005). Persuading consumers to modify their habits and adopt sustainable options requires effective strategies that convey the benefits and significance of these shifts. The incorporation of a recommendation system can play a crucial role in tracking user preferences over time and quickly adjusting to sudden changes. Factoring in such changes can yield more precise and compelling user recommendations (Hariri et al., 2015). This technology can also facilitate behavioral changes by recommending products that promote, for instance, a healthier lifestyle, thereby positively impacting society.

- **Limited Consumer Awareness:**
  Numerous consumers may lack a comprehensive understanding of the available options, particularly in terms of sustainable alternatives (Szejda et al., 2020). Lack of knowledge regarding the advantages and practicability of adopting such options can

hinder their acceptance. According to research conducted by Joshi and Rahman (2015), only 1-3% of the market consists of sustainable products. Bridging this awareness gap becomes a crucial component of fostering market growth. An AI-powered recommendation system, equipped with information regarding individual preferences and online browsing habits, has the potential to proactively introduce consumers to sustainable alternatives.

- **Information Overload:**
  In today's information-rich world, consumers are bombarded with an overwhelming amount of data. This can result in confusion and reluctance to engage. Although informing consumers about products and services is beneficial, too much information can be counterproductive (FCA, 2016). Some markets contain an excessive amount of information, such as online reviews, which complicates the decision-making process for customers (Hu and Krishen, 2019). AI recommendation systems stand out in effectively managing this flood of information. They accomplish this by condensing the information into relevant and personalized recommendations. By analyzing past behaviors and preferences, these systems present consumers with concise, accurate, and customized information, which simplifies the decision-making process.

3. Current State and Impact of Recommendation Systems

The current state of AI-based Recommendation Systems is characterized by the complexity of their underlying algorithms. These algorithms analyze vast quantities of data, including the user's browsing history, purchase patterns, preferences, and demographics, to generate personalized recommendations. Content-based filtering and collaborative filtering are two types of recommendation algorithms (University of York, 2023). Content-based filtering generates recommendations by analyzing the attributes or characteristics of an item. In contrast, collaborative filtering utilizes data from all platform users and functions similarly to word-of-mouth recommendations.

Among the wide variety of AI technologies, the Recommendation System is the most suitable option for the technology transfer. This alignment is based on the distinctive attributes and capabilities that Recommendation Systems brings to the table, making them ideally suited to address the problem domain and opportunities associated with this technology transfer initiative. To overcome issues such as disengagement and consumer behavior change, strategic advising and actions are required. Recommendation Systems have shown proficiency in influencing user behavior by presenting options that correspond to their preferences (Chinchanachokchai, 2021). In addition, these systems can play a crucial role in enhancing product awareness by introducing consumers to better choices that they may have overlooked. They can provide customized solutions that resonate on a personal level with consumers, bridging the gap between awareness and action effectively. To mitigate information overload, they are adept at providing clear and relevant options that simplify complex decisions. Recommendation Systems has been recognized for over a decade as the answer to AI's most pressing challenge, the abundance of data and algorithms (Chaudhry and Dhawan, 2020). It had played a significant role in the fields of E-Commerce, Dating Applications, social media, Digital Marketing, and Entertainment, among others, by providing users with personalized recommendations based on their preferences and choices (Verma and Sharma, 2020). By employing AI, recommendation systems enhance the user experience, increase user engagement, and propel business growth across a variety of markets, making the transfer of this technology extremely advantageous (Nvidia, 2023). The prevalence of recommendation systems is on the rise, with applications in a variety of markets (Gatzioura et al., 2019).

The impact of recommendation systems can be observed in numerous markets, including the entertainment industry. Reportedly, a significant 80 percent of Netflix movie viewings are prompted by recommendations. In addition, homepage recommendations account for 60 percent of YouTube video clicks (Zhang et al., 2019). The Entertainment industry is further impacted by AI recommendations, as music streaming platforms like Spotify use these systems to increase podcast consumption. This plan has resulted in a significant increase of 28.9% in the average number of podcasts streamed per user (Holtz, 2020).

The technology transfer of AI-based Recommendation System from one market to another has yielded substantial impacts, with its most remarkable influence being evident within the e-commerce market. Table 1 highlights the impact of personalized recommendations on the e-commerce market.

Table 1: Impact of AI-based Recommendation System in E-Commerce Market

Impact	Statistics
Usage of recommendation systems	71% of e-commerce websites (Skovhøj, 2022)
Revenue Impact	31% of e-commerce site revenue (Barilliance, 2023)
Sales Volume	Over 30% of Amazon Sales Volume (Cui et al., 2020)
Conversion Rate	70% higher conversion rate (Garcia, 2018)
Average Order Value (AOV)	21% increase in AOV (Skovhøj, 2022)
User Engagement	More than 50% (Deloitte, 2019)
Shopping Cart Abandonment	5 times more likely to make a purchase (Ding, 2019)
Upselling	40% purchased more expensive (Gilliland, 2020)
Customer Retention	56% become repeat buyers (Segment, 2023)
Marketing Spend Efficiency	10-30% increase (Boudet et al., 2019)

The following points will reflect on the impacts highlighted in Table 1.

- **Usage of Recommendation Systems:**
  Around 71% of e-commerce websites have implemented AI-based product recommendation systems, and the proportion is even higher in the Nordic countries,

with up to 90% of users discovering recommendations on the homepage. This exemplifies the extensive adoption of these systems (Skovhøj, 2022).

- **Revenue Impact:**
  AI-driven personalized product suggestions play a crucial role in boosting revenue. According to a report by Barilliance (2023), 31% of total e-commerce site revenue was generated by customized product recommendations.

- **Sales Volume:**
  By displaying products that are relevant for specific consumers, recommendation systems encourage users to explore a wider variety of offerings, thereby boosting sales. Amazon's recommendation system accounted for more than 30% of total sales volume (Cui et al., 2020).

- **Conversion Rate:**
  Optimization of conversion rates is the most important objective for e-commerce businesses. A study demonstrates the effectiveness of personalized recommendations, which led to a 70% higher conversion rate (Garcia, 2018). This increase in conversion demonstrates the influence of personalized recommendations on consumer decision-making.

- **Average Order Value (AOV):**
  Recommendations powered by AI affect not only the frequency of purchases, but also the average order value. Studies indicate an increase in AOV of 21% and basket size of 31% (Skovhøj, 2022).

- **User Engagement:**
  According to research by Deloitte (2019), more than half of consumers are more likely to make unplanned purchases when presented with personalized recommendations. This engagement not only increases sales but also strengthens the relationship between the business and the consumer.

- **Shopping Cart Abandonment:**
  The ongoing challenge for e-commerce businesses is to reduce shopping cart abandonment. According to research conducted by Salesforce, individuals who interact with recommendations are 4.5 times more likely to add items to their shopping carts and have a fivefold increase in the likelihood of completing a purchase (Ding, 2019).

- **Upselling:**
  Upselling is a strategy that encourages customers to purchase more expensive items or additional products. Approximately 40% of American consumers state that they have

purchased an item that was more expensive than they had intended because the experience felt tailored to their preferences (Gilliland, 2020).

- **Customer Retention:**
  By consistently providing value through customized recommendations, businesses increase customer loyalty and promote repeat business. Approximately 56% of customers say they will become repeat purchasers after receiving customizations, a 7% increase year-over-year (Segment, 2023).

- **Marketing Spend Efficiency:**
  By focusing marketing efforts on the delivery of personalized content, businesses increase their return on investment. According to McKinsey, using recommendation systems increases marketing-spend efficiency by 10 to 30% (Boudet et al., 2019).

The effectiveness of recommendation systems in the e-commerce industry is noteworthy, and the preceding problems faced by the e-commerce market are comparable to those faced by emerging markets, such as sustainable consumption. Implementing a content-based filtering recommendation system can aid in recommending sustainable products based on the preferences of the user. The transfer of this recommendation system technology from the e-commerce market to an emerging market can play a crucial role in addressing market gaps and creating new market opportunities.

4. Market Opportunity

Transferring established technologies and solutions to new markets paves the way for the development of innovative products or services that fill gaps or improve existing offerings. The transfer of recommendation system technology represents a transformative opportunity for many emerging markets, with **sustainable consumption** being a prominent instance. In recent years, the focus on sustainability has increased, and within this context, sustainable consumption has emerged as a market poised for rapid expansion. Current consumption patterns are acknowledged to be unsustainable, leading to a gradual shift towards promoting new, more sustainable practices (Sesini et al., 2020). Notably, according to NielsenIQ (2022), 78 percent of American consumers place a high value on sustainable lifestyles. In addition, the McKinsey US consumer sentiment survey reveals that over sixty percent of respondents are willing to pay a premium for products with environmentally friendly packaging (Feber et al., 2020). Nielsen reports that 48% of American consumers are modifying their consumption habits to reduce their environmental impact (Gelski, 2019). Furthermore, products containing Environmental, Social, and Governance (ESG)-related claims have shown a remarkable average cumulative growth rate of 28% over the past five years. In contrast, products without such ESG-related characteristics experienced a 20% growth rate (Frey et al., 2023). These impressive statistics illustrate the vast and promising market potential inherent in the growing consumer demand for sustainable consumption.

In accordance with the rise in consumer demand, the increase in environmental concerns strengthens the enormous market potential. The Sustainable Development Goals of the United Nations have highlighted the importance of sustainable consumption and production in achieving global sustainability goals. Governments and regulatory bodies are implementing policies and regulations aimed at promoting sustainability on a global scale. These measures include carbon pricing, targets for the adoption of renewable energy, initiatives to reduce waste, the introduction of eco-labeling, and incentives such as tax reductions for environmentally friendly products. These actions encourage consumers to choose these product categories and promote the adoption of sustainable consumption behaviors (Quoquab et al., 2019). Leading corporations are integrating sustainability into their business strategies. Unilever (2019) indicates that its Sustainable Living Brands have outpaced the rest of the business, with a 69% higher growth rate and accounting for 75% of the company's overall growth.

Although the sustainable consumption market is in its early stages and offers promising prospects, it faces problems such as a lack of consumer awareness and limitations on personalization, among others. Moreover, since individuals are still adjusting to sustainable consumption practices, access to relevant information becomes a crucial factor in persuading customers to adopt these behaviors (White et al., 2019). Research demonstrates that utilizing innovative technologies can improve the distribution of sustainability-related information to consumers while also addressing other related concerns (Bashir, 2022). In addition, the global market for sustainable consumption is gaining momentum, but its current status varies by region. Therefore, the significance of employing innovative technologies, such as recommendation systems, to comprehend consumer preferences and encourage sustainable consumption practices becomes even more pronounced.

5. Research Methodology

5.1 Title

Technology Transfer of AI-based Recommendation System from E-Commerce Market to Sustainable Consumption Market

5.2 Research Aim and Objectives

The research aims to explore the **potential of transferring AI-based recommendation systems** from well-established markets, particularly the e-commerce market, to the emerging sustainable consumption market. The project intends to investigate the effectiveness of implementing recommendation systems to promote sustainable consumption practices, as well as how technology transfer can address the challenges confronting the sustainable consumption market.

The following are the primary objectives of the research:

- To examine the acceptance of recommendation systems in the sustainable consumption market.
- To assess the challenges and gaps in the sustainable consumption market that can be addressed through the technology transfer of recommendation systems.
- To evaluate the impact of recommendation systems on consumer behavior, engagement, and decision-making.
- To determine the feasibility of adapting and implementing AI-based recommendation systems in the sustainable consumption market.
- To analyze the potential market opportunities and benefits generated by the technology transfer of recommendation systems in the sustainable consumption market.

Some of the research questions are as follows:

- How do consumers in the sustainable consumption market perceive and accept recommendation systems as a tool for guiding their purchasing decisions towards more sustainable choices?
- What specific challenges and gaps exist within the sustainable consumption market that can potentially be mitigated through the technology transfer of recommendation systems?
- How do recommendation systems influence consumer behavior, engagement levels, and decision-making processes within the context of sustainable consumption market?
- To what extent is it feasible to adapt and implement AI-based recommendation systems within the sustainable consumption market, considering factors such as technological compatibility and consumer readiness?
- What are the potential market opportunities and benefits that arise from the technology transfer of recommendation systems to the sustainable consumption market, and how might they impact market growth?

The following research hypotheses will be tested to provide answers to the research questions.

- The acceptance and utilization of recommendation systems in the sustainable consumption market positively correlate with consumers' inclination towards making sustainable choices.
- The technology transfer of recommendation systems can effectively address identified challenges and gaps within the sustainable consumption market, contributing to its overall improvement.
- The implementation of recommendation systems significantly impacts consumer behavior by increasing engagement, fostering informed decision-making, and encouraging more sustainable consumption practices.

- The feasibility analysis will reveal that adapting and implementing AI-based recommendation systems within the sustainable consumption market is practical and aligned with the market's current state.
- The technology transfer of recommendation systems to the sustainable consumption market will generate new market opportunities, stimulate growth, and contribute to market expansion.

5.3 Research Onion

This research will primarily employ a **secondary data collection** approach. It will include the collection of existing statistical information, reports, studies, and scholarly articles pertaining to recommendation systems, e-commerce, sustainable consumption, and technology transfer. The collected data will be carefully analyzed to comprehend the current state of recommendation systems, the hurdles faced by the sustainable consumption market, and the potential impacts of technology transfer. Data will be obtained from credible academic journals, industry reports, market research firms, and appropriate online databases. The analysis will involve comparing findings, identifying trends, and drawing conclusions based on prior studies. The analysis of secondary data will provide valuable insights into the potential benefits and challenges of transferring recommendation systems to the sustainable consumption market.

The Research Onion depicted in the figure 2 illustrates the methodologies selected for the research project.

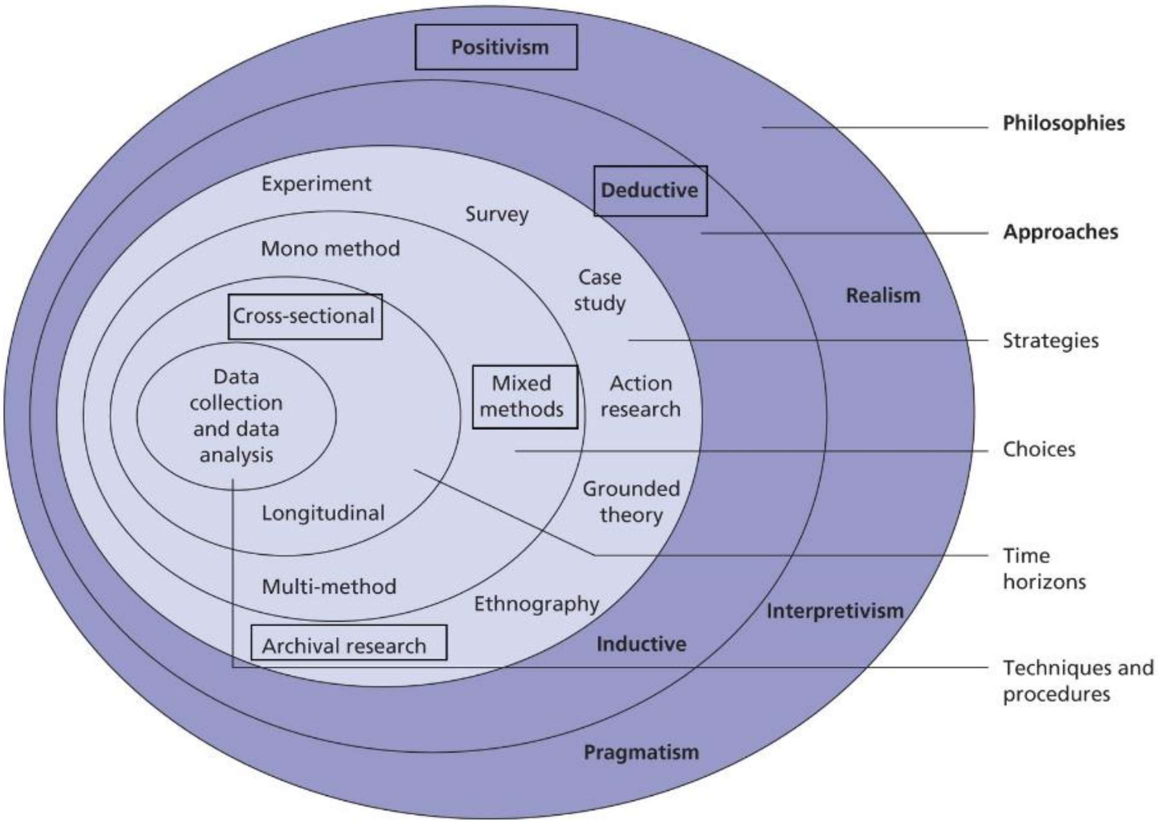

Figure 2: Research Onion

- **Research Philosophy**
  - Choosing **positivism** aligns with this study as it seeks to objectively explore the potential of technology transfer of recommendation systems to the sustainable consumption market. By analyzing existing data, trends, and impacts, the study aims to provide empirical insights into the research topic.

- **Research Approach**
  - The research employs a **deductive** approach by beginning with established theories on recommendation systems, e-commerce, and sustainable consumption. It tests the applicability of the hypotheses within the context of technology transfer and provides a structured framework to direct the analysis.

- **Research Strategy**
  - **Archival research** is well-suited for this study, which primarily relies on secondary data sources such as academic journals, industry reports, and market research studies. By reviewing and synthesizing these existing sources, the study aims to draw conclusions and generate insights.

- **Data Analysis**
  - A **mixed-methods** approach can collect quantitative data such as statistics on consumer behavior, market trends, and the impact of recommendation systems, as well as qualitative data such as expert opinions on feasibility and challenges, among others.

- **Time Horizon**
  - The **cross-sectional** approach suits this study, as it seeks to shed light on the current state, challenges, and potential benefits of technology transfer. By analyzing existing data from different sources, the study captures a snapshot of the sustainable consumption market and its relationship with recommendation systems.

5.4 Research Limitations

Some of the research limitations are as follows:

- **Limited Control Over Data Collection:** Since the research primarily relies on existing data, there is limited control over the data collection process. This lack of control could restrict the ability to address specific research questions and hypotheses in depth.
- **Outdated Information:** Given that secondary data might be sourced from various time periods, the research might not capture the most recent developments, trends, or changes in the sustainable consumption market or recommendation system technology.

6. Implementation

The implementation of the technology transfer of AI-based recommendation system to the sustainable consumption market will be based on three areas. They are described as follows.

6.1 Waste Management Recommendations

The world faces an escalating waste crisis that necessitates innovative solutions. In 2020 alone, a staggering 2.24 billion tonnes of solid waste were generated across the globe, averaging 0.79 kilograms per person per day (World Bank, 2022). The challenge is expected to intensify as populations surge and urbanization continues to rise, with an alarming projected increase of waste generation by 73% from 2020 to 3.88 billion tonnes in 2050 (World Bank, 2022). Approximately 33% of the world's waste is mismanaged, leading to adverse environmental impacts (Silpa et al., 2018). To effectively combat this challenge, a promising avenue emerges through the implementation of a waste management recommendation system. This system not only has the capability to monitor the quantity of waste produced by households but also presents valuable strategies to mitigate waste generation.

At the heart of this innovation is the integration of ultrasonic and load measurement sensors into trash cans. Placing an ultrasonic sensor on top the bin allows for the precise measurement of the waste's height, offering real-time information on waste accumulation. Concurrently, load measurement sensors carefully positioned at the bottom of the trash can continually monitor the incremental addition of waste over time. This data-rich approach provides an accurate representation of waste accumulation patterns within households (Rahman et al., 2022). In conjunction with AI image recognition technology, this information enables the classification of distinct waste types (Cheema et al., 2022). Infrared sensors are also capable of identifying different kinds of plastics such as expanded polystyrene, polypropylene, and rubber (Lynred, 2021). This capability can assist in monitoring plastic usage and subsequently offer recommendations to promote sustainable consumption.

A mobile application becomes the agent for advancement by transforming this data-driven insight into actionable recommendations. Users can effortlessly monitor their waste production and receive individualized recommendations for waste reduction. This strategy makes users active participants in the struggle against excessive waste. Visualizing the path from waste generation to waste reduction empowers users to make informed consumption decisions. The mobile application provides users with real-time insights and customized guidance, fostering a sense of responsibility and environmental awareness.

The potential for waste reduction extends beyond individual households. The data collected from multiple users can be aggregated and analyzed on a larger scale by leveraging cloud computing. By transmitting this information to a server in the cloud, a comprehensive overview of waste trends, consumption patterns, and effective reduction strategies is generated. This centralized repository enables real-time monitoring on a larger scale and affords the opportunity to offer collective advice to communities, regions, or even nations. The figure 3 depicts the working diagram of this waste management recommendation system, showcasing the integration of ultrasonic and load measurement sensors, data transmission to mobile applications, and the potential for cloud-based data aggregation and advice dissemination (Rahman et al., 2022).

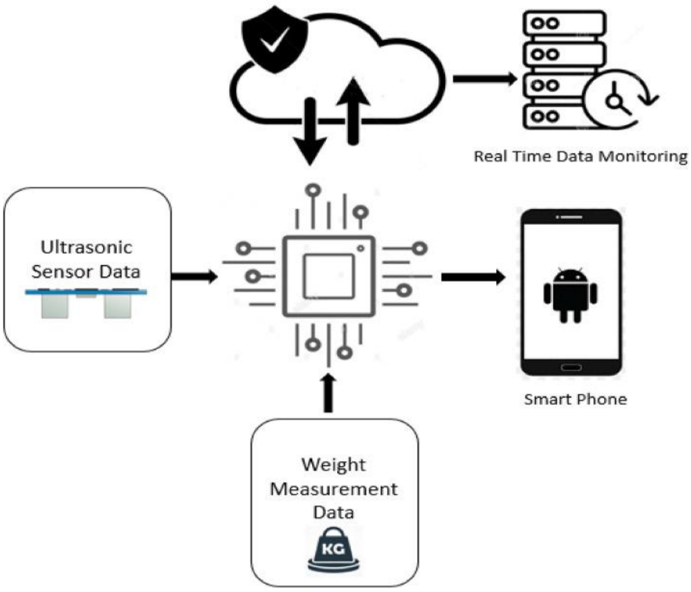

Figure 3: Waste Management Recommendation System (Rahman et al., 2022)

6.2 Sustainable Product Recommendations

Consumer awareness is crucial to promoting the adoption of sustainable products, and its absence presents a formidable obstacle. According to research conducted by Deloitte (2023), an astounding 48% of consumers attribute their reluctance to adopt sustainable lifestyles to a lack of information. Recommendation systems, which utilize the power of data to bridge the gap between consumers and sustainable consumption, are centered on bridging this gap. According to an Accenture (2018) survey, 63% of consumers prefer to buy from purpose-driven brands that promote sustainability. In addition, the global market for sustainable packaging is anticipated to reach $503.43 billion by 2030, expanding at a CAGR of 6.5% from 2023 to 2030 (Grand View Research, 2023). This demonstrates the immense potential of the sustainable consumption market. Figure 4 depicts the common recommendation process.

Figure 4: Product Recommendation Process

- **Data Aggregation:**
  At the core of sustainable product recommendations lies the collection of user data generated through interactions with e-commerce platforms. This encompasses a wide spectrum of activities, including historical browsing patterns, search inquiries, product engagements, and past purchasing behavior. The technology employed to gather such data involves tracking cookies, user accounts, and seamless integration with e-commerce interfaces.

- **Transforming Data into Insights:**
  Once the data is gathered, recommendation systems employ advanced data analytics and machine learning algorithms to derive meaningful insights. These insights unveil patterns that align with sustainable consumption choices, identifying correlations between user behaviors and preferences for specific sustainable products.

- **Tailored Recommendations:**
  The recommendation systems then translate these insights into personalized recommendations tailored to individual user preferences. These recommendations serve as virtual guides, assisting users in navigating the complexities of adopting sustainable practices. By aligning recommendations with users' past selections, the system maximizes resonance and user engagement.

In addition, information overload is a frequent barrier for consumers in the context of sustainability. The recommendation system addresses that by incorporating clearly defined sustainability criteria. This criterion encompasses a variety of sustainability characteristics, such as certifications, endorsements, material sourcing, energy efficiency, ethical practices, and social accountability measures, among others. The adaptable nature of the recommendation system ensures that it remains in tune with the evolving preferences of consumers and the ever-changing landscape of sustainable product offerings. As consumer behavior changes and new eco-friendly products emerge, the system seamlessly modifies its recommendations to account for these alterations.

6.3 Energy Consumption Recommendations

In the pursuit of a more sustainable lifestyle, energy conservation emerges as an essential aspect. National Energy Action (2023) asserts that the magnitude of this crisis is unimaginable, highlighting the urgency of this matter. As of October 2021, 4.5 million households in the United Kingdom were struggling with fuel poverty, demonstrating the terrible effects of energy shortage. According to US Energy Information Administration (EIA) projections, energy consumption in the building sector, which includes both commercial and residential structures, is expected to increase by a significant 65% between 2018 and 2050 (Shrestha, 2020). This context emphasizes the central importance of energy consumption and the imperative necessity of addressing it.

In this landscape, the recommendation system emerges as a powerful tool for fostering sustainable energy consumption practices. By employing data-driven insights, this system can influence and guide users towards making energy-efficient choices that not only contribute to personal savings but also alleviate the strain on global energy resources. At the foundation of this strategy is the collection of energy consumption data from individual users. This is accomplished by monitoring and analyzing their paid utility bills and appliances closely. The system captures various facets of energy consumption, including utilization patterns, peak usage hours, billing cycles, and historical consumption trends. Users have the option of authorizing the recommendation system to access their energy bills and home appliances, or connecting their utility accounts for automated data retrieval. This ensures a seamless and privacy-aware approach to data collection, respecting users' preferences while allowing the system to generate insightful data. After collecting the data, the recommendation system conducts an extensive analysis. By recognizing patterns and behaviors, the system identifies potential energy savings areas. It identifies peak usage hours, energy-intensive appliances, and opportunities to reduce energy consumption. The methods for extracting patterns from energy consumption data are presented in Table 2.

Table 2: Pattern Extraction Methods

Pattern Type	Item-sets	Method
Abnormal appliance usage	The use of an appliance over time	Change in consumption by percentage (Sial et al., 2021)
Peak energy consumption slots	Consumption of power per time slot	Manual classification (Sial et al., 2014)
Associations of on or off instances with time intervals	Appliances that are switched on or off based on a time slot	Association rule mining (Alsalemi et al., 2020)

By detecting abnormal usage of particular appliances over time, deviations from normal consumption patterns could be identified. The percentage change method computes the percentage change in energy consumption over time for specific appliances. A sudden and significant increase or decrease in consumption relative to historical data may indicate abnormal consumption (Sial et al., 2021). A manual classification method can be used to identify specific time intervals during which energy consumption is at its peak. Manually categorizing different time slots based on their energy consumption levels can aid in identifying peak hours and provide more precise results. By analyzing historical consumption data, it is feasible to identify time slots with consistently high consumption (Sial et al., 2014). Association rule mining can be used to discover associations between instances in which appliances are turned on or off and specific time intervals. This involves employing data mining techniques to identify common patterns or associations between the on/off instances of appliances and their respective time intervals. By analyzing the data, consumers can determine which appliances tend to be utilized during particular time periods (Alsalemi et al., 2020).

Beyond specific recommendations, the system is equipped to provide users with general tips and best practices for energy conservation. These tips span various aspects of daily life, such as electricity usage, air conditioning and heating strategies, insulation techniques, water consumption management, and energy-efficient practices. Users can access these personalized recommendations and conservation tips through a user-friendly interface. Alternatively, they can receive them through email notifications, ensuring that the guidance seamlessly integrates into their daily routines. This approach fosters user engagement, empowers informed decision-making, and encourages the adoption of sustainable energy consumption techniques.

7. Challenges involved in the Technology Transfer

Transferring recommendation systems across markets, especially from e-commerce to sustainable consumption, presents both opportunities and challenges. The challenges associated with the process of transferring recommendation system technology to the sustainable consumption market are summarized in Table 3.

Table 3: Challenges involved in the Technology Transfer

Challenges	Description
Diverse Consumer Preferences	Due to factors such as personal values, cultural background, and socioeconomic standing, consumer preferences for sustainable products and practices are extremely diverse (Capgemini, 2020). For instance, some individuals may priorities purchasing locally sourced products to support their communities, while others may priorities purchasing products with minimal packaging to reduce waste. To address this challenge, recommendation systems must incorporate advanced machine learning techniques capable of accurately capturing and interpreting complex consumer preferences. Collaboration with behavioral psychologists and sociologists can shed light on how different demographic groups respond to recommendations for sustainable consumption.
Limited Data Availability	In the sustainable consumption market, gathering comprehensive and reliable data poses a significant challenge. Unlike e-commerce platforms where products are well-documented, sustainable products often lack standardized information. This deficiency may include incomplete product descriptions, limited images, and

	varying categories. Furthermore, as sustainable consumption is a relatively nascent field, the volume of user-generated content, such as reviews and ratings, might be insufficient (Consumers International, 2023). This deficiency hinders the capacity of recommendation systems to generate accurate insights into consumer preferences, resulting in potentially fewer effective recommendations. This challenge necessitates novel approaches to data collection, which may involve partnerships with manufacturers of sustainable products, the utilization of open data initiatives, and the application of advanced data augmentation techniques to compensate for data gaps.
Complex Sustainability Criteria	The concept of sustainability encompasses a wide range of criteria, such as environmental impact, ethical sourcing, societal responsibility, and fair business practices (Zhang et al., 2022). Incorporating these complex and diverse criteria into recommendation algorithms necessitates the formulation of suitable indicators, the determination of weighting factors, and the establishment of clear evaluation standards for measuring product sustainability. In the context of a recommendation system, it can be difficult to strike a balance between these diverse and sometimes contradictory factors. The system must intelligently evaluate each criterion and provide recommendations that are consistent with the user's preferences while adhering to sustainability principles.
Data Privacy and Trust	In any recommendation system, ensuring user trust and data privacy is of the utmost importance. A common reluctance among users to share personal data, such as energy usage patterns or financial information, is a fear of misuse or unauthorized access. Establishing a robust framework for data privacy that includes stringent encryption, secure data storage, and transparent data handling practices is essential. A fundamental aspect of overcoming this challenge is building user confidence through transparent communication about data usage and compliance with data protection regulations (OECD, 2021). Developing mechanisms to allow users to control the data they share and providing clear opt-in options can foster confidence and encourage users to participate more willingly in the recommendation system.

8. Data Analysis

The Data Analysis section attempts to evaluate the potential of recommendation systems by examining various facets.

8.1 Technology Acceptance Model (TAM)

There is no standard performance measurement for recommender systems. A study conducted by Roy and Dutta (2022) examined 60 papers, of which 21 utilized recalls, 10 utilized mean absolute error, 25 utilized precision, 18 utilized F1-measure, 19 utilized accuracy, and 7 utilized root-mean-square deviation to calculate system performance. Hence, in addition to the performance of a recommendation system, user acceptance is a crucial factor to consider. Using the Technology Acceptance Model (TAM) to evaluate the user acceptance of a recommender system can provide more precise information regarding user satisfaction. With 116 participants, an experiment was conducted to identify the factors that contribute to the technology acceptance model (Armentano et al., 2015). Included were the ability to use a recommendation system, the perceived ease of using a recommendation system, the perceived usefulness of the technology, and the acceptability of the technology for use in different domains. Participants' statistics are presented in table 4 (Armentano et al., 2015).

Table 4: Participants' Statistics

Attribute	**Variable**	**Rate**	**Amount**
Sex	Male	63.8%	74
	Female	36.2%	42
Age Range	20-30	76.7%	89
	30-40	14.7%	17
	More than 40	8.6%	10
Area of Expertise	Business	32.8%	38
	Computer Science	34.5%	40
	Economics	17.2%	20
	Others	15.51%	18

The statements given to participants and the corresponding TAM variable are outlined below (Armentano et al., 2015). They responded using a Likert scale, with 1 representing "strongly disagree" and 5 representing "strongly agree."

- Ability: I believe I have the ability to use recommendation systems to obtain useful recommendations.
- Perceived Ease of Use: I found the recommendation system easy to use.
- Perceived Usefulness: The technology used by the recommendation system is accurate.

- Acceptance: I would use other recommendation system in a different domain.

Cronbach's Alpha was calculated to determine the data's reliability. Figure 5 depicts the Cronbach's Alpha for all the factors, and it can be seen that it is greater than 0.7 for all the factors, indicating that the data is sufficient to be regarded as appropriate and reliable.

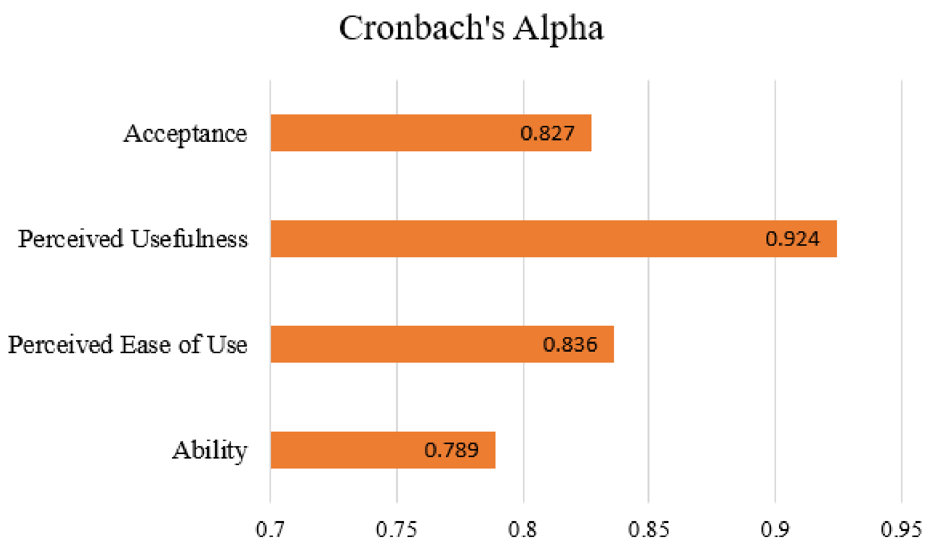

Figure 5: Cronbach's Alpha

In addition to establishing reliability, it is necessary to determine the correlation between factors. Component matrix from factor analysis is used to determine how the observed parameters contribute to the underlying factors. Positive numbers denote a positive relationship between the parameter and the factor, while negative numbers denote a negative relationship. Figure 6 demonstrates, for instance, that "Perceived Ease of Use" has a high positive loading of 0.909 on the "Ease of use" factor. This indicates a strong positive relationship between the parameter "Perceived Ease of Use" and the factor underlying the ease of use of recommendation systems (Armentano et al., 2015).

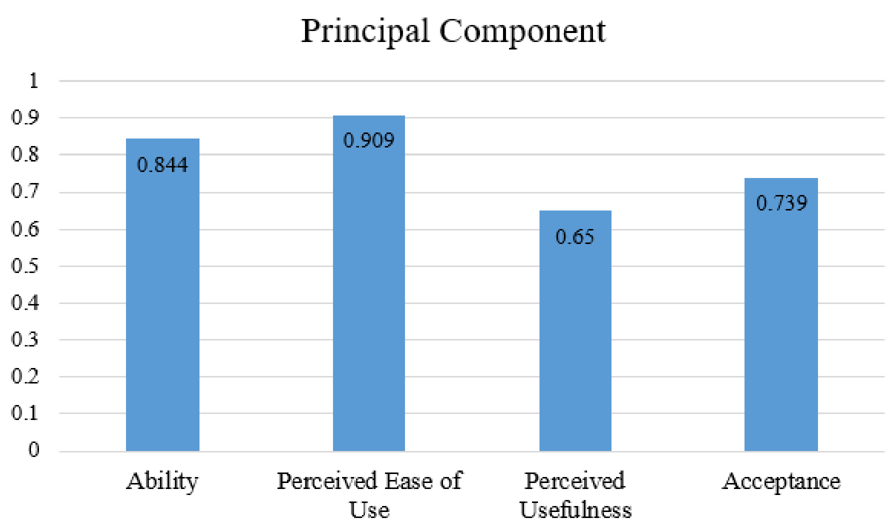

Figure 6: Factor Analysis

In the sustainable consumption market, where user acceptance plays a pivotal role in the success of recommendation systems, the TAM model emerges as a valuable tool. By comprehensively assessing users' perceptions and attitudes, the model enhances our understanding of how individuals engage with and embrace sustainable consumption practices facilitated by recommendation systems. When consumers lack the proficiency to navigate the technology efficiently, it can deter them from using it further, ultimately impacting its overall adoption. As evidenced by Figure 6, it becomes apparent that individuals have a confident belief in their ability to utilize recommendation systems adeptly. Additionally, the substantial loading of perceived ease of use signifies that these systems are perceived as straightforward and user-friendly. In the realm of the sustainable consumption market, the significance of ease of use is even more pronounced. This significance suggests that a user-friendly system can significantly boost its adoption.

Although the perceived usefulness metric may rank slightly lower compared to other factors, it still registers as high. This suggests that individuals who face challenges in making purchase decisions for products or services perceive the technology as valuable and accurate. In the context of the complex sustainability criteria of the sustainable consumption market, the notion that individuals find the recommendation system accurate holds substantial implications. Moreover, a factor analysis load of 0.739 in the context of acceptance vividly indicates people's willingness to apply recommendation systems across diverse domains. Hence, it can be deduced that the utilization of recommendation systems by individuals is feasible in the context of the sustainable consumption market.

Baier and Stüber (2010) undertook another research study that explored the acceptance model of recommendation systems. This study involved 100 students, comprising 65 males and 35 females. The age of the participants ranged from 19 to 32 years, with an average age of 24.1 years. Table 5 presents the component loadings derived from the statements used in the course of the experiment.

Table 5: Component Loadings

Factor	**Statement**	**Component Load**
Quality of Output	The recommended products meet what I want	0.851
	The recommended products satisfy my needs	0.877
Perceived Ease of Use	It is simple to acquire more information	0.923
Perceived Usefulness	The recommendations are helpful to me	0.908
Purpose of Use	I utilize recommendations for shopping	0.840
Usage Habit	I use recommendations frequently	0.812

The data presented in table 5 illustrates that the recommendation system not only fulfills consumer requirements but also aids users in easily acquiring desired products (Baier and Stüber, 2010). Furthermore, individuals frequently engage with and utilize recommendation systems, including for shopping purposes. This indicates that the recommendation system holds the potential to make a significant impact in the sustainable consumption market, given its resemblance to attributes found in shopping markets. Based on the aforementioned findings, it can be inferred that recommendation system technology has been widely accepted across various domains for several years due to its user-friendly nature and perceived usefulness. As a result, there is a strong probability that this technology will gain acceptance in the sustainable consumption market as well.

8.2 Analysis of Smart Dustbin for Waste Management Recommendations

The implementation of the waste management recommendation necessitates the development of a smart dustbin with load measurement and ultrasonic sensors. Despite the fact that it sounds appealing, it is important to examine how individuals perceive intelligent trash cans. This will aid in determining whether or not individuals intend to utilize such trash cans, allowing for the creation of customized recommendations. Recent research conducted by Liu and Hsu (2022) indicates that environmental concern, perceived usefulness, perceived playfulness, perceived ease of use, and intention to use are motivational factors for using smart trash bins. A total of 230 individuals participated in the study, with males constituting 33.9% and females making up the remaining 66.1% of the sample. Approximately 63.5% of the participants fell within the age bracket of 31 to 45 years. In terms of engagement with smart recycling systems, 46% of the respondents reported having utilized such systems. Among this group, 20.4% used the systems less than once a week, followed by 14.8% who used them once a week, and a minor 1.3% who used them daily. Conversely, a majority of 53.9% of the surveyed residents disclosed that they had never employed smart recycling systems. The component loadings of the factors and the data's reliability are depicted in Figure 7 (Liu and Hsu, 2022).

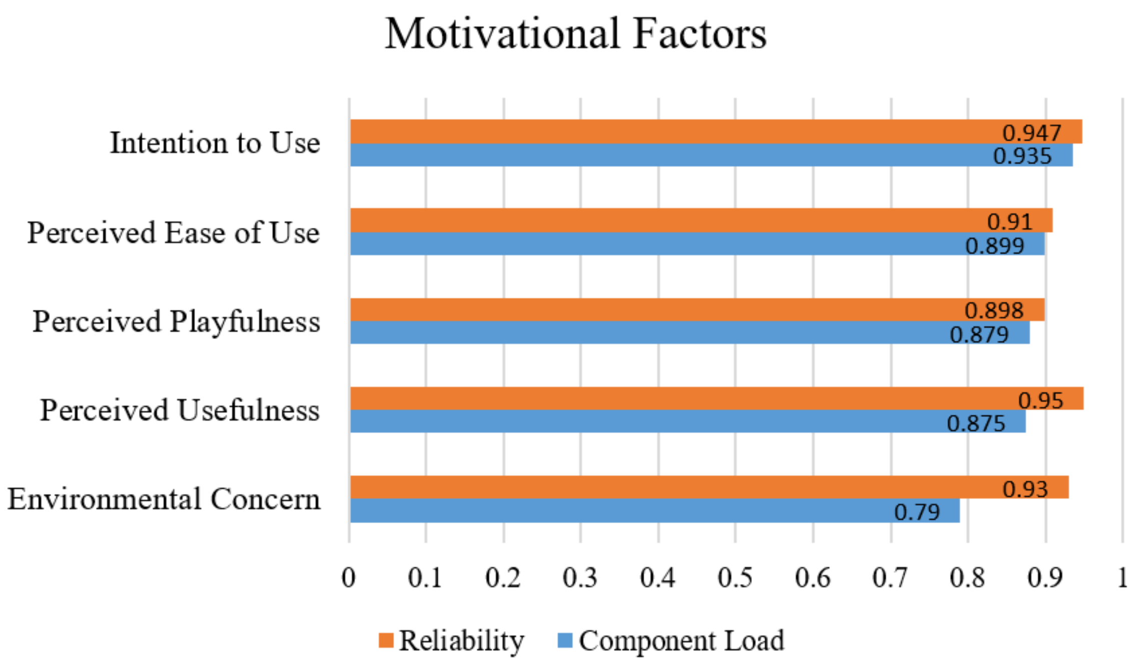

Figure 7: Motivational Factors

The reliability of all the mentioned factors, as evidenced in Figure 7, exceeds the threshold of 0.7, confirming the presence of valid and dependable data. The environmental concern, a motivational factor, mirrors the impact of excessive waste on individuals' inclination to utilize smart dustbins. The figure unequivocally illustrates that a heightened awareness of environmental preservation and the adverse effects of waste encourages people, increasing the likelihood of smart dustbin usage. Perceived usefulness gauges the extent to which an individual believes that employing a specific system would enhance their task performance. The notable component loading of 0.875 undeniably signals that individuals perceive smart dustbins as valuable tools. Perceived playfulness encompasses people's perception of technology interactions as engaging and intriguing. It encompasses personal enjoyment, psychological stimulation, and interest. From the illustration in Figure 7, it is evident that smart dustbins manage to captivate consumers' interest, generating fascination with their use.

Perceived ease of use pertains to individuals' perception of the minimal physical and mental effort required when utilizing a particular system or technology. It is advisable for perceived ease of use to carry a high component loading, as a straightforward and user-friendly technology reduces the burden to learn. The figure 7 strongly suggests that smart dustbins are designed for consumer convenience, as they are perceived to be easily manageable. The overarching motivational factor centers on the intention to use the technology. A substantial component loading of 0.935 clearly underscores people's motivation to employ smart dustbins within the sustainable consumption market. Hence, utilizing such smart dustbins enables recommendation systems to gather data and provide tailored suggestions to individuals regarding waste management.

Furthermore, alongside individuals' perceptions of using intelligent waste bins, the accuracy of these bins also holds significant importance. According to the approach detailed in the implementation, the precision of classification was computed at 95.3125%, while the System Usability Score (SUS) was employed to assess user satisfaction, resulting in a score of 86% (Rahman et al., 2022). Additionally, figure 8 provides an overview of the individual precision levels for various waste detection categories. The VGG16 method was selected for this purpose, as it is widely recognized for its application as a feature extractor in diverse computer vision tasks, encompassing image classification and object detection (Cheema et al., 2022).

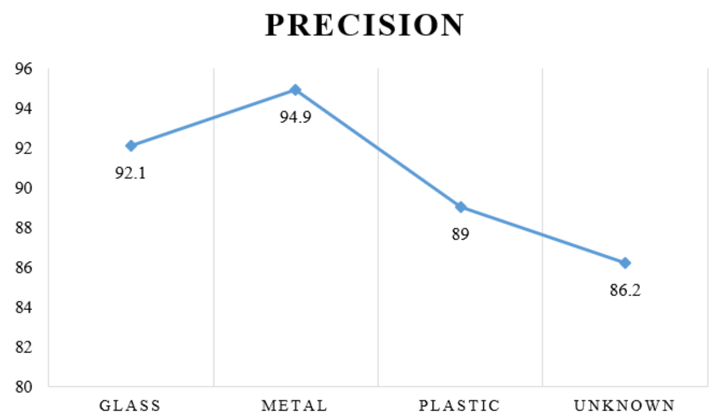

Figure 8: Precision

The high precision values illustrated in figure 8 indicate a more dependable waste classification process. When the smart dustbin undertakes the task of categorizing waste items, there exists a high probability that the assigned category is accurate. This greatly enhances the efficacy of waste management practices. In the context of waste management, misclassifying waste can lead to improper disposal and hinder recycling initiatives. These precision values work to minimize such errors. This enables the smart dustbin to offer tailored recommendations based on the identified waste category. The precision of classification ensures that users receive relevant guidance for sustainable disposal and recycling methods. Consequently, this fosters a sense of trust among users in the capabilities of the smart dustbin. Consumers are more likely to embrace and actively engage with the technology of the recommendation system when they observe such accurate waste classification and pertinent recommendations.

8.3 Analysis of the Impact of Product Recommendations

Research indicates that recommendation systems have a positive impact on both product views and conversion rates for purchases (Lee and Hosanagar, 2021). Various research studies have been carried out to support this assertion. For instance, Kumar and Hosanagar (2019) conducted a study to examine the impact of recommendation systems on the number of product views.

Throughout the duration of the experiment, a total of 37,619 distinct products were hosted on the website. Among these, the pages of 32,173 products (accounting for 85 percent of all products) were visited during various visitor sessions. In total, there were 1,307,191 visitor sessions where at least one product page was viewed. Among these sessions, 434,353 (33.30 percent) corresponded to the control version, 435,411 (33.31 percent) belonged to the treated version, and the remaining 436,437 (33.39 percent) were not included in the experiment. The control version, in this context, pertained to the group that remained unaltered and received the customary treatment, whereas the treated version referred to the group that was exposed to product recommendations. The control version was employed as a benchmark against which the influence of the recommendation system on product views was assessed by comparing it with the treated version. Both versions of recommendations were randomly assigned to visitor sessions with equal likelihood. To evaluate the efficacy of product recommendations, an analytical breakdown was performed on visitor sessions, focusing on the sequences of product page views. As a result, a total of 2,326,402 product page views were collected across 869,764 visitor sessions. Figure 9 provides a visual representation comparing the product page views in both the control and treated versions (Kumar and Hosanagar, 2019)

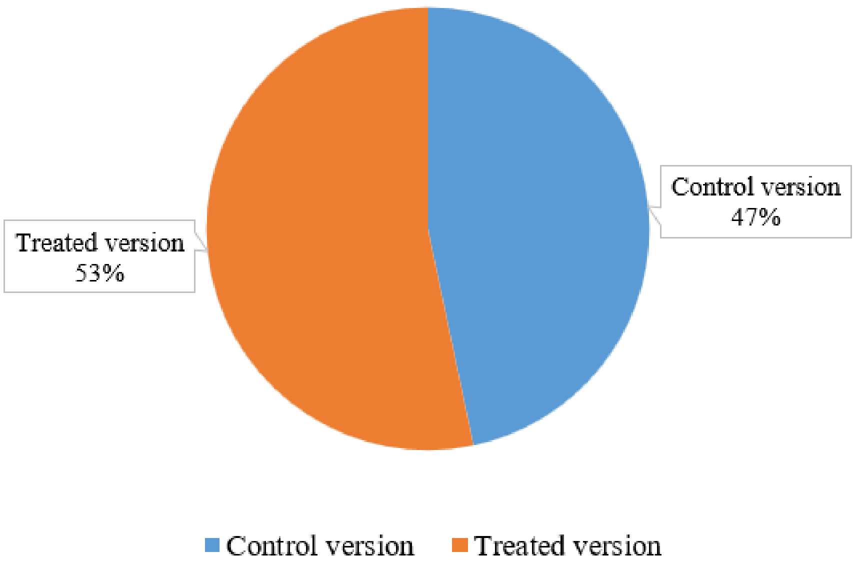

Figure 9: Product Page Views

Among the total of 2,326,402 product page views, 1,086,222 (accounting for 47 percent) were associated with control sessions, while 1,240,180 (constituting 53 percent) belonged to treated sessions. Evidently, there is a noticeable distinction in the number of product page views per session between the treated and control versions. This observation signifies that the treated version, empowered by the recommendation system technology, experienced a higher frequency of product page views in comparison to the control version. This shift implies that the enhanced visibility of pertinent products within the treated version, facilitated by the recommendation system, effectively reduces the costs associated with searching for products, thereby fostering a more substantial exploration of various product offerings.

Another research endeavor was conducted by Lee and Hosanagar (2019) with the aim of investigating the impact of product recommendations on the purchasing activities of consumers. This particular study was conducted on the Canadian website of a major retailer ranked among the top five in North America. The experiment encompassed a comprehensive spectrum of product categories available on the website, spanning 82,290 distinct SKUs, and involved the participation of around 1,138,238 unique users. To ensure the robustness of the data, a testing platform was employed, which implemented sophisticated cross-device customer identification strategies. These strategies amalgamated multiple factors such as IP addresses, cookies, log-in information, and more, along with algorithmic techniques like customer matching, to assign a unique visitor ID to each customer. This approach ensured that even if customers interacted with the website using various devices for purchases or browsing, their identity was accurately identified and data repetition was avoided. Purchase-based collaborative filtering was the method utilized for generating recommendations, and the purchase logs of individual customers were meticulously recorded. Figures 10 and 11 illustrate the impact of recommendation system technology on purchasing behavior by comparing control and treated versions. Similar to the prior experiment, the control version represented the unaltered state, while the treated version experienced exposure to the recommendation system technology (Lee and Hosanagar, 2019).

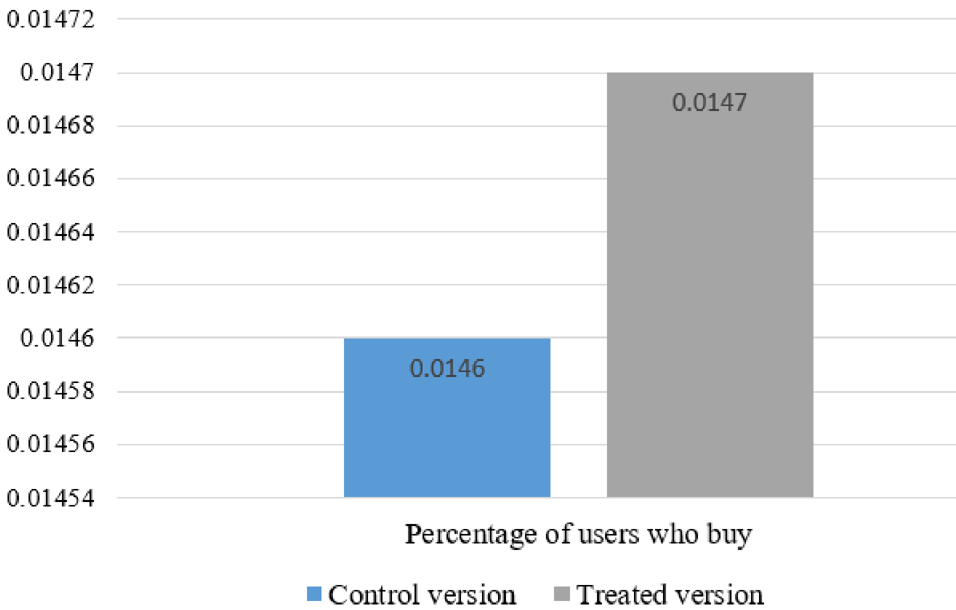

Figure 10: Percentage of users who buy

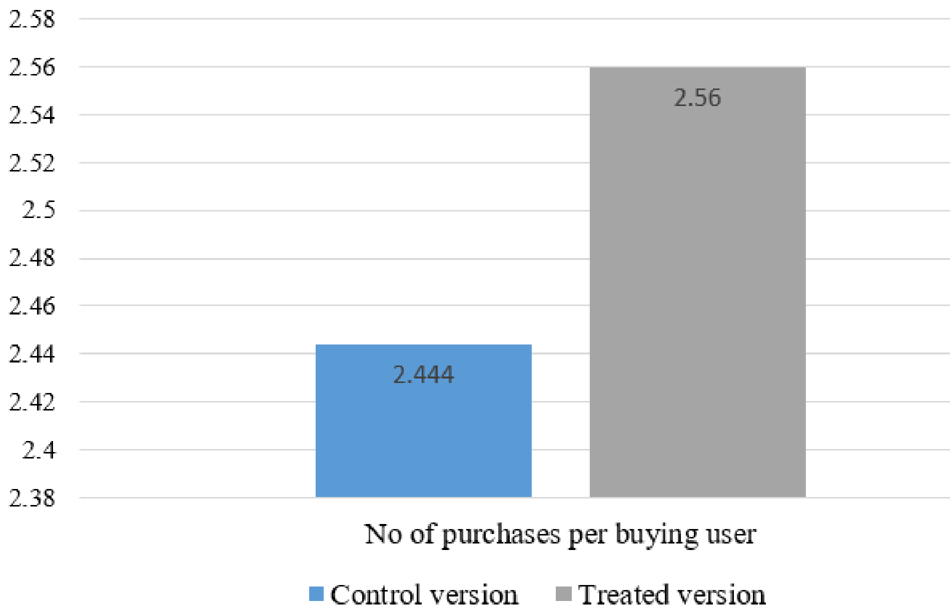

Figure 11: No of purchases per buying user

The impact of the recommendation system on purchase activity is distinctly evident as it leads to a positive shift in either the percentage of users making purchases, the average number of purchases per user, or even both. As the sustainable consumption market continues to gain traction, the introduction of a recommendation system stands poised to generate favorable outcomes, not solely in terms of heightened product views, but also by catalyzing purchase activities. A rise in the percentage of users engaging in purchases can potentially expand the customer base, opening doors for future growth and extended market reach.

Concurrently, an increase in the average number of purchases per user could foster loyalty towards sustainable consumption, consequently boosting sales within the realm of sustainable products. The enhanced product views hold the power to propagate awareness regarding sustainable consumption among individuals. Furthermore, this heightened engagement with products directly tackles some of the core challenges faced by the market. Additionally, this strategic approach could address the issue of information overload, guiding customers towards placing trust in the recommendation system due to the tailor-made personalization it offers. This, in turn, could drive higher purchase activities, thereby amplifying both market size and revenue streams.

The experiment conducted by Lee and Hosanagar (2021) offers several valuable insights that should be taken into account when implementing AI-based recommendation systems in the sustainable consumption market. These insights are presented in Table 6. Hedonic products are those that are consumed for enjoyment, pleasure, or sentiments, whereas utilitarian products are those that are consumed to fulfil a particular need (Basso et al., 2019).

Table 6: Insights

Attribute	**Insights**
(Hedonic & Utilitarian) x Views	The impact of the recommendation system on product views is greater for utilitarian than hedonic products.
(Hedonic & Utilitarian) x Purchase	The impact of the recommendation system on product purchase conversion is greater for hedonic than utilitarian products.
Price x Views	Higher prices increase the impact of the recommendation system on product views.
Price x Purchase	Higher prices decrease the impact of the recommendation system on product purchase conversion.
Review Volume x (Views & Purchase)	The impact of a recommendation system on product views and purchase conversion rises as the number of customer reviews increases.

The insights derived from Table 6 offer valuable considerations for the sustainable consumption market. For instance, sustainable products that align with a purpose-driven approach to environmental protection are likely to receive more product page views. While the impact of the recommendation system on purpose-driven sustainable products might be relatively lower than that on products centered around pleasure, this impact can still be amplified by recognizing the influence of pricing on purchase conversion. Ensuring competitive and reasonable prices can attract a broader consumer base, as the recommendation system tailors suggestions to individuals with similar pricing preferences. This strategy not only drives consumer engagement but also contributes to boosting overall market revenue. Furthermore, prompting customers to share their reviews and experiences with sustainable products can foster awareness and trust within the market. The data derived from customer reviews holds the potential to refine recommendation algorithms, resulting in more precise and relevant product suggestions. This process not only enhances the customer experience but also generates positive word-of-mouth and endorsements for the recommendation system in the realm of sustainable consumption.

8.4 Analysis of the Impact of Energy Consumption Recommendations

A study was conducted concerning energy consumption recommendations, which aimed to introduce a framework for assisting households in enhancing their energy usage through real-time guidance for efficient appliance utilization (Eirinaki et al., 2022). This framework enables the generation of energy consumption profiles tailored to individual households and specific appliances by analyzing patterns of appliance usage. The Non-Intrusive Load Monitoring (NILM) technique was employed to analyze energy consumption and the operational status of individual appliances based on primary meter readings. This method involves making estimations about the appliances being used and calculating the energy consumption of each appliance by examining fluctuations in voltage and power readings from the main power supply. The term "non-intrusive" signifies that no external devices are required for this analysis.

Following the data collection process, pattern extraction methodologies like association rule mining and manual classification, similar to those mentioned in previous energy consumption recommendation implementations, were employed. These techniques aid in identifying events such as turning appliances on or off, identifying abnormal usage patterns, and more. To capture more detailed insights into appliance usage, a time interval of 30 minutes was utilized (Eirinaki et al., 2022). To formulate recommendations, a dataset encompassing electricity consumption data from five households collected over periods ranging from 3 months to 3 years, as compiled by Kelly and Knottenbelt (2015), was employed. This dataset contained both overall household mains power demand and specific appliance-level power demand readings for all five houses. The dataset included information about 25 individual appliances, providing ample data for generating accurate recommendations.

Recognizing the uniqueness of each household's energy consumption patterns, each house was treated as a distinct case study. As mentioned earlier, a NILM approach was applied to streamline the data. Subsequently, frequently used appliances that were activated during different time segments were integrated into the recommendation system at 30-minute intervals. As a demonstration of the concept, a web application featuring a dashboard was developed, enabling users to monitor their household's energy consumption and appliance usage. Furthermore, a customizable panel was integrated to present the recommendations. The findings of the study for four households, encompassing details about energy usage and the energy savings resulting from the implementation of recommendation systems, are summarized in Table 7 (Eirinaki et al., 2022).

Table 7: Energy Usage

House	Total Consumption (Wh)	Total Energy Saved (Wh)	Energy Saved (%)
2	31935.8	1612.52	5.04
3	1005.86	173.32	17.23
4	11658.71	236.51	2.03
5	44788.08	1345.47	3

Four households, each with distinct characteristics regarding recording duration, appliance count, and daily energy usage, were selected for the study. The research also asserts that the algorithm's accuracy in predicting appliance usage is substantiated by achieving a high recall rate. Following the recommendations and complying with the prompt to turn off appliances could potentially result in energy savings ranging from 2% to 17% (Eirinaki et al., 2022. These findings are consistent with a recent study, which suggests that users who actively engage with recommendation systems can lead to more than a 30% reduction in building energy consumption, with average savings reaching around 20% (Ramallo-González et al., 2022). These statistics underscore the positive impact of implementing energy consumption recommendation systems in promoting energy conservation and facilitating sustainable living practices.

Energy consumption recommendations have been developed over the years using various strategies, and one of these strategies involves utilizing social norms. The data collected from a multitude of households is aggregated and then centralized into a repository. This repository is utilized to distribute information about energy consumption patterns within neighborhoods or even larger geographical areas. This data sharing mechanism serves to keep individuals informed about whether their energy usage falls above or below the local average, thereby encouraging a more sustainable approach. Tailored recommendations can be generated based on individual consumption patterns and neighborhood trends. A similar study was conducted to explore the impact of social norms on energy consumption behavior (Schultz et al., 2018). In this experiment, individual energy usage data and average neighborhood energy consumption data were shared with each household in the region. The objective was to analyze how energy usage changed among households that exceeded or fell below the average energy consumption. The hypothesis was that households using more energy than the average would reduce their consumption, contributing to sustainability. On the other hand, those consuming less than the average might increase their usage, which posed a potential challenge. To address this, an additional message with emoticons was sent to some households. Positive emoticons were used to express appreciation for consuming less than the average, while negative emoticons conveyed disappointment for exceeding the average. This research encompassed 287 households and spanned a duration of two weeks for energy consumption data collection. Figure 12 displays the findings of the study using color-coding indicators (Schultz et al., 2018).

Type of Household	Change in Daily Energy Consumption	
	Without Emoticons (Message)	With Emoticons (Message)
Above Average Household		
Below Average Household		

Indicator		Decrease in Energy Consumption
		Increase in Energy Consumption
		Similar to earlier Energy Consumption

Figure 12: Change in Energy Consumption

The findings in Figure 12 clearly illustrate that households exceeding the average neighborhood energy consumption tend to reduce their energy usage when presented with comparative consumption data. Conversely, households consuming less energy than the neighborhood average often increase their energy usage in response to such comparisons. Nevertheless, when these households receive appreciative emoticons and customized messages, they continue to practice energy conservation and sustainable behavior. This highlights the significance of personalized messaging. Given that recommendation systems are renowned for providing personalized suggestions and messages, their potential to positively impact the sustainable consumption market is considerable. Furthermore, based on the aforementioned analysis, it becomes evident that recommendation systems should prioritize incorporating more personalized messages and tips to enhance consumer engagement in sustainable behavior. Providing recommendations solely based on others' consumption patterns can lead to conflicting signals, underscoring the need for careful implementation and a focus on maximizing personalization.

8.5 Analysis of the Issues of Recommendation Systems

Recommendation systems have demonstrated a favorable influence across various markets, notably in the e-commerce market, and their potential for yielding positive effects in the sustainable consumption market is also evident. However, alongside their beneficial outcomes, certain issues also emerge. As noted by Tariq (2022), common issues associated with recommendation systems encompass concerns related to privacy, behavior manipulation, fairness, and transparency. To assess the impact of these issues, a survey was conducted, comprising 13 questions ranging from multiple-choice inquiries to checkboxes, thereby enabling a more comprehensive understanding of the issues at hand. The survey garnered 54 valid responses, of which 72.5% were contributed by male respondents and 27.5% by female respondents.

Considering the aspect of privacy within data collection practices that facilitate personalized recommendations, nearly half of the users (48.3%) express a preference to avoid such personalization due to concerns about sensitive information exposure. Additionally, it becomes evident that users' expectations regarding privacy protection are not sufficiently met through the existing Terms of Service (ToS). Notably, a significant majority (75%) of respondents seek the capability to actively manage user profiling. Turning to the element of transparency, approximately 50.3% of participants reveal that their decision to share data is contingent on their level of trust in a specific website (Tariq, 2022). When it comes to sharing data with third parties, the majority (58.3%) lean towards complete non-disclosure, while a sizeable proportion (30%) are open to data sharing as long as their information remains anonymous. Within the context of fairness, an interesting 35% of participants believe that some level of bias is acceptable in recommendation systems, recognizing its potential advantages for businesses. For addressing such biases, half of the participants (50%) advocate for user-configurable settings to control bias, while 21.7% believe that recommendation systems should be devoid of any bias. In relation to behavior manipulation, the majority of participants (51.9%) favor giving users the autonomy to enable or disable censorship within recommendation systems (Tariq, 2022).

These statistics collectively highlight the pronounced concerns users have regarding these issues, which could influence their receptiveness to adopting recommendation systems. Such concerns might extend to the sphere of sustainable consumption market, casting potential negative implications on consumer behavior. Nonetheless, through the implementation of robust data regulations, adherence to ethical guidelines, and maintaining transparency, the positive aspects of integrating recommendation systems within the realm of sustainable consumption can potentially outweigh these apprehensions.

9. Business Aspect

The following business aspects will include a brief description of the business plan for implementing an AI-based recommendation system in the sustainable consumption market.

- **Market Analysis:**
  Thorough market research can be undertaken to identify target segments within the sustainable consumption market, such as enthusiasts of eco-friendly products, health-conscious consumers, and socially responsible businesses. Analyzing consumer behavior, preferences, and buying patterns related to sustainable products and services can provide insights to offer accurate recommendations and enhance user engagement.

- **Business Form and Strategy:**
  Establishing an independent platform or collaborating with existing sustainable brands can be explored for integrating the recommendation system. Developing a business strategy that emphasizes personalization, user empowerment, and sustainability is essential. Partnerships can also be established with eco-friendly brands to provide exclusive deals and promotions.

- **Finance:**
  Diverse revenue streams like subscription-based models, referral commissions from partner brands, and sponsored content can be identified. Additionally, assessing initial development costs, integration expenses, marketing budgets, and ongoing maintenance expenditures are crucial for financial planning. Offering a free basic version of the recommendation system that suggests energy consumption or waste management methods can attract users and drive user acquisition.

- **Legal Compliance and Human Resources:**
  Addressing data privacy concerns can involve ensuring full compliance with data protection regulations and implementing transparent user consent mechanisms. Assembling a multidisciplinary team consisting of AI developers, data privacy experts, legal advisors, and customer support personnel is essential to navigate legal intricacies and sustain user demand.

- **Business Roadmap:**
  Creating a clear roadmap outlining the integration process, user onboarding strategy, and potential challenges is pivotal. A phased rollout plan, accompanied by user training sessions, proactive customer support, and continuous improvements based on user feedback, ensures a smooth implementation journey.

The integration of AI-based recommendation systems into the sustainable consumption market offers immense business potential. By understanding consumer segments and their preferences, the market analysis opens avenues for targeting specific needs. Collaborations with sustainable brands extend reach and credibility. Diverse revenue streams ensure financial sustainability. Legal compliance ensures user trust and data protection. Building a skilled team ensures smooth operations and support. A well-structured roadmap guarantees successful implementation, leading to enhanced user engagement and market expansion. This amalgamation presents substantial business opportunities and benefits for sustainable growth in the market.

10. Project Management

Throughout the duration of the project, weekly meetings were held to monitor progress and solicit supervisor feedback to maintain the project's quality. Furthermore, project plans were developed during the initial phase to conduct a systematic literature review and secondary data collection. To fulfill the research requirements, an extensive range of resources including research articles, academic journals, industry reports, and relevant sources were meticulously reviewed on a weekly basis. In parallel with the literature review and data collection, weekly reports were diligently composed. These reports served as a crucial tool for monitoring the project's advancement, tracking the milestones achieved, and addressing any potential roadblocks.

11. Conclusion & Recommendations

This research contributes by exploring the potential of AI-based recommendation systems through their transfer from the e-commerce market to the emerging sustainable consumption market. This process of technology transfer not only creates new opportunities within sustainable consumption but also effectively addresses crucial challenges that include low awareness levels, disengagement, information overload, lack of personalization, and the complex nature of behavioral change. While recommendation systems have already demonstrated their impact across various industries, their most profound influence has been observed in the e-commerce sector. On the other hand, the sustainable consumption market is still in its early stages. As we bridge the gap between e-commerce and sustainable consumption, a multitude of opportunities emerge, empowering consumers to make conscientious and environmentally conscious choices.

The implementation of recommendation systems can be targeted towards three key areas: waste management recommendations, sustainable product recommendations, and energy consumption recommendations. However, the journey of transferring this technology is not without challenges. Addressing data privacy concerns and grappling with limited data availability stand as significant obstacles that must be navigated. The research methodology, centered on the collection of secondary data, draws from diverse sources to facilitate comprehensive data analysis, uncovering the potential implications of this technology transfer. The results of the secondary data analysis indicate a clear positive impact of recommendation systems on product views and purchases, underscoring their potential to drive favorable outcomes within the sustainable consumption market. Furthermore, the data analysis sheds light on individuals' perceptions of waste management and energy consumption strategies, further solidifying the feasibility of introducing recommendation systems to the sustainable consumption market. In the process of implementing these systems, it is recommended that businesses place emphasis on aspects such as ensuring robust data privacy measures, enhancing user accessibility and proficiency in utilizing the systems, enabling personalized customization, and fostering collaborative partnerships with sustainable brands. Moreover, a continuous process of monitoring user behavior, adhering to stringent data and legal regulations, and a commitment to iterative improvement are vital for the sustained success of these systems. Future research endeavors could explore behavioral assessment, user categorization, and quantifying the ecological influence, thereby contributing to a comprehensive understanding of the technology's effectiveness and impact. In conclusion, the path of transferring AI-based recommendation systems from the well-established e-commerce sector to the emerging sustainable consumption market holds immense promise and offers practical solutions to a multitude of challenges.

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