# Capstone Project Proposal

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## Business Goals

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| **Project Overview and Goal**<br><br>What is the industry problem you are trying to solve? Why use ML/AI in solving this task? Be as specific as you can when describing how ML/AI can provide value. For example, if you're labeling images, how will this help the business? | **Industry Problem:**<br>The primary challenge is the current e-commerce platforms' inability to deliver highly personalized shopping experiences. This limitation negatively affects customer satisfaction, loyalty, and restricts revenue and market share growth.<br><br>**Why Use ML/AI:**<br>ML/AI is crucial for this task because it can analyze extensive customer data to predict and recommend products that closely match individual preferences and buying history. The value of ML/AI in this scenario includes:<br><br>- **Personalization at Scale:** Automating tailored product suggestions for each customer, something not achievable manually.<br>- **Continuous Improvement:** ML/AI models improve their recommendations over time, enhancing customer satisfaction and loyalty.<br>- **Business Impact:** By boosting personalization, ML/AI directly contributes to increased sales, repeat business, and overall revenue growth.<br><br>In essence, ML/AI offers a strategic solution to enhance customer experience and achieve business objectives by leveraging data-driven insights for personalized recommendations. |
| **Business Case**<br><br>Why is this an important problem to solve? Make a case for building this product in terms | Addressing the lack of personalized shopping experiences on e-commerce platforms is crucial for enhancing customer satisfaction and loyalty, which are pivotal drivers of business success. By implementing an AI-powered recommendation engine that accurately |

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| of its impact on recurring revenue, market share, customer happiness and/or other drivers of business success. | predicts and suggests products based on a customer's previous purchases, businesses can significantly improve the shopping experience. This improvement is expected to lead to higher levels of customer engagement and retention, directly contributing to an increase in recurring revenue and market share. Moreover, happy customers are more likely to become repeat buyers and advocates for the brand, further amplifying the positive impact on the company's growth and competitive position in the market. Solving this problem not only strengthens customer relationships but also sets a foundation for sustainable long-term success. |
| **Application of ML/AI**<br><br>What precise task will you use ML/AI to accomplish? What business outcome or objective will you achieve? | We will use ML/AI to tailor product recommendations based on individual customer purchase history, aiming to increase customer retention and boost sales. |

# Success Metrics

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| **Success Metrics**<br><br>What business metrics will you apply to determine the success of your product? Good metrics are clearly defined and easily measurable. Specify how you will establish a baseline value to provide a point of comparison. | Success will be measured by increases in customer retention rates, average order value (AOV), and customer lifetime value (CLV). Baseline values will be established by analyzing historical data on these metrics prior to implementing the AI-powered recommendation engine, providing a clear point of comparison to gauge the impact of personalized recommendations. |

# Data

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| **Data Acquisition**<br><br>Where will you source your data from? What is the cost to acquire these data? Are there any personally identifying information (PII) or data | Data will be sourced from the H&M Personalized Fashion Recommendations dataset on Kaggle, featuring anonymized customer transactions and product information, at no direct acquisition cost. While the dataset is pre-anonymized to mitigate PII concerns, sensitivity in handling and extending this data with respect to privacy laws remains paramount. The dataset represents a static batch that will require periodic |

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| sensitivity issues you will need to overcome? Will data become available on an ongoing basis, or will you acquire a large batch of data that will need to be refreshed? | refreshing with new data to maintain the recommendation engine's relevance and accuracy. |
| **Data Source**<br><br>Consider the size and source of your data; what biases are built into the data and how might the data be improved? | The H&M Personalized Fashion Recommendations dataset on Kaggle, sourced from H&M's transaction records, product catalog, and customer information, is extensive, reflecting the shopping patterns and preferences of H&M's customer base. However, inherent biases may arise from this dataset:<br><br>1. **Demographic Bias:** If H&M's customer base is not diverse, the data may overrepresent certain demographic groups, leading to recommendations that are not as effective for underrepresented groups.<br>2. **Geographic Bias:** The dataset may reflect preferences specific to the regions where H&M operates, potentially limiting its applicability in markets with different fashion trends and consumer behaviors.<br>3. **Temporal Bias:** Fashion trends evolve, and historical data might not accurately predict future preferences. The data's relevance can diminish over time without regular updates.<br>4. **Item Bias:** Popular items in the dataset might be over-recommended, overshadowing potentially relevant but less popular products, leading to a narrower range of suggestions.<br><br>**Improving the Data:**<br><br>- **Diversifying Data Sources:** Incorporating data from a wider range of sources, including different regions and demographics, can help mitigate biases and create a more inclusive recommendation system.<br>- **Regular Updates:** Periodically refreshing the dataset with recent transactions can help the model adapt to evolving fashion trends and consumer preferences.<br>- **Balancing the Dataset:** Techniques like oversampling underrepresented categories or artificially augmenting data for less popular items can help reduce item bias and improve the diversity of recommendations. |

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| | - **Bias Mitigation Algorithms:** Implementing algorithms designed to identify and mitigate biases in the data can help ensure more equitable and effective recommendations.<br><br>By addressing these biases and continuously improving the dataset, the recommendation engine can better serve a diverse customer base and adapt to changing market dynamics. |
| **Choice of Data Labels**<br>What labels did you decide to add to your data? And why did you decide on these labels versus any other option? | **Chosen Data Labels:**<br><br>1. **Purchase History (e.g., frequency, recency, and monetary value):** Labels that capture aspects of the customer's purchase behaviour are critical for understanding their buying patterns and predicting future purchases.<br>2. **Customer Demographics (e.g., age group, gender):** Although the dataset is anonymized, broad demographic labels can help tailor recommendations to demographic segments, improving the relevance of suggestions.<br>3. **Seasonality (e.g., spring, summer, fall, winter):** Fashion preferences often change with seasons, making seasonality an important label for predicting which items a customer is more likely to purchase at different times of the year.<br>4. **Product Ratings & Reviews**: Including labels for customer feedback on products can help refine recommendations based on the popularity and satisfaction levels associated with each item.<br>**Rationale for Choice:**<br>These labels were chosen over others because they provide a comprehensive view of both customer behaviour and product characteristics, which are essential for personalizing recommendations. They balance the need for personalization with the constraints of data privacy by focusing on general patterns and preferences rather than on sensitive personal details.<br>**Versus Other Options:**<br>Other potential labels, such as explicit personal identifiers or highly specific purchase details, were not considered to maintain privacy and comply with data protection regulations. Additionally, focusing on too niche labels could limit the generalizability and scalability of the recommendation engine across diverse customer bases and product ranges. The selected labels offer a balanced approach, aiming to maximize recommendation relevance while ensuring ethical use of data. |

# Model

| **Model Building**<br><br>How will you resource building the model that you need? Will you outsource model training and/or hosting to an external platform, or will you build the model using an in-house team, and why? | Building the model for personalized product recommendations involves significant considerations regarding expertise, resources, and operational efficiency. The decision to outsource model training and hosting or to build the model using an in-house team hinges on several factors:<br><br>**Option 1: Outsourcing Model Training and/or Hosting**<br>**Pros:**<br>- Access to specialized expertise and state-of-the-art technologies without the need for extensive internal training.<br>- Potentially faster deployment times, as external platforms are optimized for AI/ML development.<br>- Scalability and reliability, with managed services handling spikes in demand and ensuring high availability.<br>**Cons:**<br>- Higher long-term costs due to subscription fees and service charges.<br>- Potential risks around data privacy and security, especially when handling sensitive customer information.<br>- Less control over the model's development and updating process.<br><br>**Option 2: Building the Model In-House**<br>**Pros:**<br>- Complete control over the development process, allowing for customizations specific to business needs.<br>- Enhanced data security, as all customer data remains within the organization's control.<br>- Potential cost savings in the long term, especially if the organization already possesses or is willing to invest in the necessary infrastructure and expertise.<br>**Cons:**<br>- Initial higher upfront investment in technology and talent acquisition.<br>- Longer ramp-up time for development, especially if building from scratch or the team is inexperienced in AI/ML.<br>- Ongoing maintenance and updates require sustained commitment and resources. |
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| | **Decision and Rationale:**<br>Given the importance of the recommendation engine to the business's success and the sensitivity of customer data involved, an **in-house development approach** is advisable if the organization has or can develop the requisite AI/ML capabilities and infrastructure. This approach prioritizes data security, customizability, and long-term cost efficiency. However, if the organization lacks the immediate expertise or infrastructure and seeks rapid deployment, partnering with an external platform for model training and hosting, while ensuring strict data handling agreements, could be a strategic initial step. The decision ultimately rests on balancing the trade-offs between control, cost, expertise, and speed to market. |
| **Evaluating Results**<br><br>Which model performance metrics are appropriate to measure the success of your model? What level of performance is required? | For an AI-powered recommendation engine like the one proposed, using the H&M Personalized Fashion Recommendations dataset, selecting the right performance metrics is crucial to accurately assess the model's effectiveness in improving customer satisfaction and boosting sales. The following metrics are particularly relevant:<br><br>**1. Precision and Recall**<br>- **Precision** measures the proportion of recommended items that are relevant to the user.<br>- **Recall** assesses the proportion of relevant items that are successfully recommended by the model.<br>- A balance between precision and recall, possibly measured by the **F1 score**, is essential to ensure that the recommendations are both accurate and comprehensive.<br>**2. Mean Average Precision at K (MAP@K)**<br>- This metric evaluates the model's ability to rank items that the user is likely to interact with or purchase higher in the recommendation list. It's especially useful for scenarios where the order of recommendations matters.<br>**3. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)**<br>- For models that predict ratings or levels of interest, RMSE or MAE can quantify the average error between predicted and actual values. Lower values indicate better performance.<br>**4. A/B Testing Metrics**<br>- **Conversion Rate:** The percentage of users who make a purchase after receiving recommendations. |

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| | - **Average Order Value (AOV):** The average amount spent by customers who purchased through recommendations.<br>- **Customer Retention Rate:** The rate at which existing customers return to make subsequent purchases.<br>**Required Level of Performance**<br>- The specific targets for these metrics will depend on baseline measurements and industry benchmarks. However, as a general rule, the model should demonstrate a significant improvement over the current baseline or control group in A/B testing scenarios.<br>- For precision, recall, and MAP@K, performance significantly above random chance (specific numbers may vary by application, but typically aiming for precision and recall well above 0.5, and MAP@K improvements of at least 5-10% over baseline).<br>- For RMSE and MAE, values should be as low as possible, with specific targets set based on historical model performance data.<br>- For A/B testing metrics, meaningful improvements in conversion rates, AOV, and retention rates compared to control groups are required, with specific percentage improvements set based on historical performance and strategic business objectives.<br><br>Ultimately, the model's success is measured not only by its statistical performance but also by its impact on key business outcomes, such as increased sales, customer satisfaction, and loyalty. |

# Minimum Viable Product (MVP)

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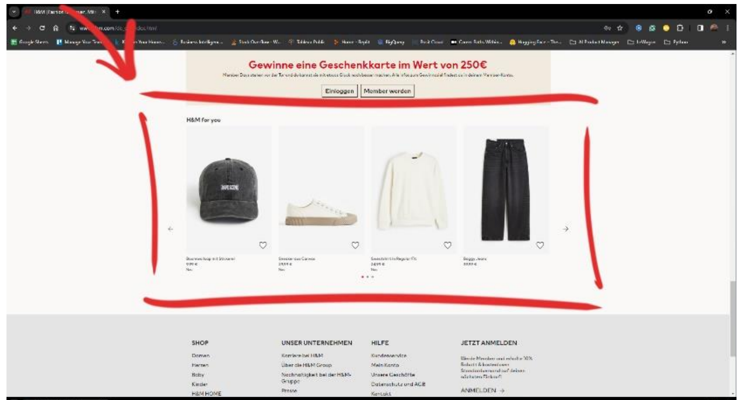
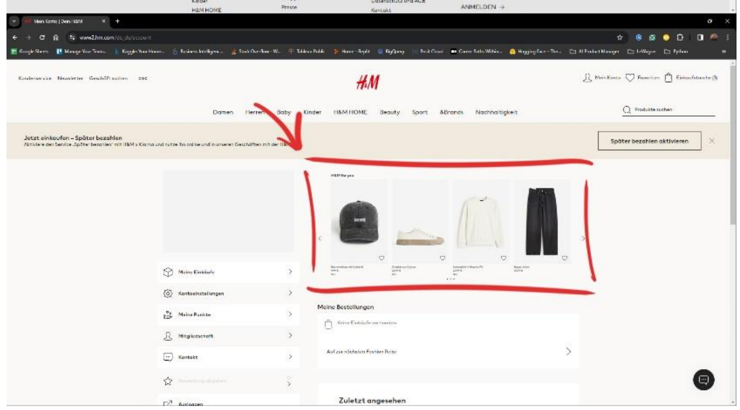
| **Design**<br><br>What does your minimum viable product look like? Include sketches of your product. | <br><br><br><br><br>The sketch above illustrates the minimum viable product (MVP) for an e-commerce platform, specifically tailored for "H&M for You," featuring an AI-powered recommendation engine. This prototype, focusing on the homepage and the user profile page, provides a user-friendly interface that includes sections for user login and personalized recommendations based on past purchases. The design strategically emphasizes the personalized recommendation section on both the homepage and the user profile page, aiming to enhance the shopping experience through efficient user interaction with the platform.<br><br>As an additional suggestion, the personalized recommendation engine could also enhance our marketing efforts, such as being featured in newsletters or notifications for users who download our app, ensuring that personalized content reaches our users across various platforms. |
| **Use Cases** | The product is designed for the "Modern Shopper" persona, characterized by the following attributes: |

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| What persona are you designing for? Can you describe the major epic-level use cases your product addresses? How will users access this product? | - **Demographics:** Aged 25-45, urban dwelling, tech-savvy with a medium to high income.<br>- **Behaviors:** Values convenience, personalization, and efficiency in shopping. Frequently shops online for a variety of products, from clothing to electronics, and prefers platforms that offer a tailored shopping experience.<br>- **Needs and Goals:** Seeks a seamless online shopping experience that saves time and offers personalized recommendations based on their tastes and previous purchases. Interested in discovering new products that fit their style and preferences.<br><br>**Epic-Level Use Cases**<br><br>1. **Personalized Shopping Experience:** Users can log in to receive personalized product recommendations, enhancing their shopping experience by showing items likely to be of interest based on past behavior.<br>2. **Efficient Product Discovery:** Through the AI-powered search and recommendation engine, users can quickly find products that meet their specific needs and preferences, reducing the time spent browsing.<br>3. **Seamless Purchase Process:** The platform offers an intuitive and straightforward purchasing process, from adding items to the cart to checking out, designed to minimize hurdles and improve conversion rates.<br>4. **Engagement and Retention:** Features like personalized offers, wish lists, and timely notifications about new items or sales aim to increase user engagement and encourage repeat visits.<br><br>The product is accessible through a responsive web interface, ensuring compatibility across various devices including desktops, laptops, tablets, and smartphones. Users can also engage via mobile apps available for iOS and Android, offering a tailored shopping experience on the go. |
| **Roll-out**<br><br>How will this be adopted? What does the go-to-market plan look | The go-to-market plan for the AI-powered e-commerce recommendation engine focuses on strategic outreach, partnerships, and user engagement to drive adoption:<br>1. **Market Research and Segmentation**<br>- Begin with in-depth market research to identify |

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| like? | target customer segments, focusing on demographics that align with the "Modern Shopper" persona. This research will guide the messaging and channels used in marketing efforts.<br>**2. Product Launch Strategy**<br>- **Soft Launch**: Initially introduce the product to a select group of users for beta testing, gathering feedback to refine features and user experience.<br>- **Official Launch**: Roll out the product with a comprehensive launch campaign, leveraging press releases, social media, influencer partnerships, and email marketing.<br>**3. Partnerships and Collaborations**<br>- Establish partnerships with fashion influencers and bloggers to promote the platform's unique selling proposition—personalized shopping experiences. Collaborate with brands and designers for exclusive launches or features on the platform to attract their followers.<br>4. **Digital Marketing and SEO**<br>- Invest in search engine optimization (SEO) and pay-per-click (PPC) advertising to increase visibility. Utilize social media platforms to engage potential users through targeted ads, engaging content, and interactive campaigns.<br>- Implement content marketing strategies, such as blogging about fashion trends and how the platform can enhance the shopping experience, to drive traffic and establish authority.<br>**5. Customer Engagement and Retention**<br>- Offer initial sign-up incentives, such as discounts or exclusive access to new products, to encourage registrations.<br>- Develop a loyalty program rewarding repeat customers with points, discounts, or early access to sales, fostering a sense of community and loyalty.<br>**6. Feedback Loop and Continuous Improvement**<br>- Continuously collect user feedback through surveys, reviews, and usage data to improve the platform and add features that address user needs.<br>- Regularly update the user base on new features and improvements, keeping the platform fresh and engaging.<br>**7. Scaling and Expansion**<br>- After establishing a strong user base in the initial target market, plan for gradual expansion into |

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| | new markets and demographics, adapting the product and marketing strategies based on local preferences and behaviors.<br><br>This go-to-market plan combines targeted marketing efforts, strategic partnerships, and a strong focus on user experience and engagement, aiming to quickly build a user base while laying the groundwork for sustained growth and adoption. |

# Post-MVP-Deployment

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| **Designing for Longevity**<br><br>How might you improve your product in the long-term? How might real-world data be different from the training data? How will your product learn from new data? How might you employ A/B testing to improve your product? | Improving the product over the long term involves a multifaceted approach, focusing on adaptation, continuous learning, and optimization. Here's how these elements can be integrated:<br><br>**Long-Term Improvements**<br>1. **Continuous Learning and Model Updating:** Implement machine learning models that can adapt to new data over time, either through periodic retraining or employing online learning algorithms that update in real-time as new data comes in.<br>2. **Feature Evolution:** Continually evaluate and evolve the features used by the model to ensure they remain relevant to current shopping behaviors and trends. This may involve adding new data sources, such as real-time social media trends or economic indicators, to better predict user preferences.<br>3. **User Experience Enhancements:** Regularly update the platform's user interface and functionality based on user feedback and behavioral data to improve usability and engagement.<br><br>**Real-World Data vs. Training Data**<br>Real-world data often diverges from training data in several ways:<br>- **Temporal Shifts:** Consumer preferences and behaviors can shift due to seasonal changes, trends, or external events, leading to differences between the static historical data used for training and the dynamic real-world data.<br>- **Data Quality and Completeness:** Real-world |

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| | data might contain more noise, inconsistencies, or missing values than the curated datasets typically used for training models.<br>- **New Categories and Products:** The introduction of new products or categories not present in the training data can challenge the model's ability to make accurate recommendations.<br><br><u>**Learning from New Data**</u><br>To ensure the model remains effective and relevant:<br>- **Periodic Retraining:** Schedule regular updates to the model with new data to incorporate recent trends and behaviors.<br>- **Feedback Loops:** Use user feedback and interaction data as a form of continuous learning, allowing the model to adjust recommendations based on what users find useful or irrelevant.<br><br><u>**Employing A/B Testing**</u><br>A/B testing is crucial for iterative improvement:<br>- **Feature Testing:** Test new features or algorithms with subsets of users to evaluate their impact on user engagement, satisfaction, and conversion rates compared to the current baseline.<br>- **Personalization Strategies:** Experiment with different personalization strategies to identify what delivers the most value to different segments of users.<br>- **UI/UX Changes:** Use A/B testing to evaluate changes in the user interface and experience, ensuring that updates contribute positively to user engagement and satisfaction.<br><br>By employing a strategy that combines continuous learning, adaptation to real-world data, and rigorous A/B testing, the product can maintain its relevance and effectiveness in the long term, continually improving to meet the evolving needs and preferences of its users. |
| **Monitor Bias**<br><br>How do you plan to monitor or mitigate unwanted bias in your model? | Monitoring and mitigating unwanted bias in the model is crucial for ensuring fairness, accuracy, and reliability of the AI-powered recommendation engine. Here are strategies to address this challenge.<br><br>1. <u>**Bias Detection and Assessment**</u><br>- **Regular Audits:** Conduct regular audits of the recommendation engine to assess and identify potential biases. This involves analyzing the |

model's predictions and recommendations for fairness and accuracy across different user groups.

- **Diverse Testing Data:** Use a diverse set of testing data that reflects the broad spectrum of users. This helps in identifying biases that the model may have towards certain groups.

2. **Bias Mitigation Techniques**

- **Algorithmic Adjustments:** Implement algorithmic fairness approaches, such as fairness constraints or re-weighting training data, to reduce bias in model predictions.
- **Feature Engineering**: Carefully review and adjust the features used by the model to ensure they do not inadvertently introducing bias

3. **Inclusive Data Collection**

- **Expand Data Sources**: Incorporate a wider range of data sources to ensure the training data encompasses a diverse set of preferences, behaviors, and demographics.
- **Anonymization and Pseudonymization**: Ensure that personal identifiers are removed or obfuscated to prevent biases associated with demographic or personal characteristics.

4. **Continuous Monitoring**

- **Feedback Loops**: Establish mechanisms for users to report instances where the recommendations may seem biased or inappropriate. This real-time feedback can be invaluable for identifying and correcting biases.
- **Performance Metrics for Fairness:** Utilize fairness-specific performance metrics to continuously monitor the model's outcomes across different groups, ensuring that no group is disproportionately advantaged or disadvantaged.

5. **Transparency and Accountability**

- **Explainability Tools:** Use tools and techniques that enhance the model's explainability, allowing stakeholders to understand how recommendations are generated and to identify potential sources of bias.
- **Documenting and Reporting:** Maintain detailed documentation of data sources, model decisions, and mitigation efforts to ensure transparency and accountability in model development and maintenance.

6. **Stakeholder Engagement**

- **Engage Diverse Perspectives:** Involve stakeholders from diverse backgrounds in the

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| | model development and review process. This can help identify potential biases and fairness issues from different perspectives.<br><br>By implementing these strategies, the goal is to create a recommendation engine that not only personalizes the shopping experience but does so in a way that is fair, unbiased, and respectful of all users' diversity. Continuous effort and commitment to these principles are essential for maintaining trust and reliability in the AI system. |