Exploring the Impact of Virtual Fitting Room Technology on Return Rates and Customer Loyalty: A randomized controlled trial with Zara

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Part 1: Research Proposal

Memo to Decision Makers

Authors: Anita Hsu 100%

Defining the result of implementing Virtual Fitting Room (VFR) technology is crucial for ZARA to reduce reverse logistics costs and unnecessary environmental waste. Since this technology was introduced, businesses have been considering the risks and returns of implementing VFR. The potential benefits of saving costs on processing excess return orders and maximizing profit by increasing customer loyalty and demand are tempting. However, how do businesses determine the level of effectiveness and rate of return?

Our study will focus on two main points: How VFR affects the return rate and the customer loyalty. Both customer loyalty and return rate are crucial for ZARA in influencing the numbers. Return rate shows whether VFR is effective in helping customers pick the right sizes, colors, and whether looks good on them. And customers' repurchase behavior, including repurchase rate, repurchase frequency and hazard rate of repurchase, will help us examine the impact of VFR technology on customer loyalty. As a business, loyal customers means more demand and stronger price elasticity among customers, making the company less vulnerable to market downturns. Furthermore, customer loyalty drives supply chain logistics, which, if managed well, can significantly reduce costs.

From ZARA's perspective, conducting this study would be both time and cost-efficient. We will collect data from online customers of ZARA. Participants will be selected and randomly assigned to either a control or experimental group. In the experimental group, customers will be fully guided on how to use the technology. Promotions for both groups will be kept identical to avoid any confounding factors. The data collection process will be straightforward since ZARA's e-commerce customer database already contains sufficient information, such as order history, purchase times, purchasing timelines, and basic customer information and preferences. It ensures no direct and personal contact between the researchers and the study subjects. We will collect data continuously over a period of six months, and all researchers involved will be meticulously trained to keep customer information confidential and secure.

By conducting sufficient statistical tests on collected data, our study can provide ZARA with clear, evidence-based insights into customer preferences and habits when using VFR technology. In addition, we simulated different scenarios of our study results in advance and provided related suggestions to each situation. These insights will support decision-making on whether investing in this technology is worthwhile for the company. Ultimately, the results could translate into significant financial advantages, environmental sustainability, and increased brand loyalty. We look forward to collaborating with you and seizing this opportunity to gain valuable data insights and realize a broader vision.

Statement of the Problem

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The emergence of a digital economy has opened up new possibilities in marketing for the clothing industry (Sun et al., 2021). Fokina (2024) thinks that the sales volume of global e-commerce is to get past $7 trillion by 2024. Unfortunately, online apparel shopping comes with a high risk of returns (Daroch et al., 2021) and one reason for this is due to fit and sizing problems. Jaya and Karunanidhi (2022) identified that repeated high returns influence the loyalty of customers, but create struggles for retailers alongside logistical, financial barriers. To solve the problem, VFR and Virtual Try-On (VTO) technologies are proposed as solutions (Kamilah et al.,2024). The technology utilizes Augmented Reality (AR) and Artificial Intelligence (AI) to allow consumers to virtually try on items before purchasing them, thus promoting purchasing decisions (Liu et al., 2020).

There has been far from agreement with existing research about the utility of virtual fitting rooms. VFR was effective on customers, but the same effect did not push up in all segments of customer types (Xiong, 2023). Whether the VFR and VTO could reduce return rate from customers and increase customer loyalty would be examined by this research through a control group experiment, supplying some practical decision basis for retailers like Zara.

Literature Review

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The first commercial use of VTO technology dates back to 2005, when Levi's launched Intellfit, a body-scanning system for selecting jeans. In 2011, Intel introduced the "Magic Mirror," an LCD monitor for visualizing clothing on users' bodies. SnapChat's popular AR filters, like adding makeup or accessories, use similar technology. In 2017, Warby Parker integrated VTO into their app, scanning users' faces to recommend glasses, with an upgraded version released in 2019 (McCarthy et al., 2021). Retailers soon expanded VTO to clothing, allowing customers to "try on" outfits virtually, eliminating the need for fitting rooms or waiting in lines.

As technology advances and customers become more comfortable with it, companies are eager to understand how VFR impacts costs and revenue. Research shows that VTO enhances the personalized shopping experience, offering customers the convenience of trying on clothes without visiting a store, and most importantly, reducing return rates. Fashion retailers such as Adidas and ASOS have implemented the technology for online shoppers with significant results (Buehler, 2024). Zeegit, an Israel-based fashion technology company, developed an app allowing users to upload full-body photos and virtually try on clothing from partner brands. Zeegit focuses on simplifying online shopping and collaborates with brands like Adidas, enabling users to purchase apparel directly. For ASOS, Zeegit facilitated photoshoots during the COVID-19 lockdown, emphasizing diverse body types. Since the pandemic, when people couldn't visit stores, VTO technology has grown exponentially. Zeegit reports a 36% decrease in return rates for its partners after introducing the technology (Biron).

From a business standpoint, reducing costs by eliminating returns is highly efficient, as the cost of processing a return often represents a large portion of the product's overall cost (Zheng, 2023).

Since redoing and repackaging returned items is costly, companies often find it more cost-effective to discard them. According to Optoro, only 20% of 3.5 billion returned products in the US are defective, meaning most returns are due to poor fit or appearance. This dissatisfaction leads to negative reviews and decreased customer trust, harming brand loyalty. Moreover, returned items that are opened or poorly packed require special handling, creating additional challenges for retailers. Most companies also lack the resources to repair minor defects, such as a rip on a t-shirt, making disposal the more practical option (Constable).

Unfortunately, many nearly-new clothing items end up in landfills, and the carbon emissions from this process are equivalent to those produced by three million cars. It is estimated that the return logistics industry accounts for 15 million metric tons of CO2 emissions annually, equivalent to the energy use of nearly 2 million homes (Tait, 2023). The transportation, plastic packaging, and refurbishment processes required to make returned items "resellable" all contribute to environmental damage. Understanding how effective VTO is in providing more accurate fit information is essential, as reducing returns not only lowers costs but is also better for the environment.

While existing studies show the potential of VFR to improve shopping experiences, there is limited experimental evidence on its long-term impact on brand loyalty and repurchase behavior. Our study aims to fill this gap by investigating the relationship between VFR adoption, reduced return rates, and customer loyalty in the clothing industry.

In this research, we aim to examine return rates and customer loyalty. Our goal is to identify solutions that help differentiate the brand. For a clothing retailer like ZARA, which faces strong competition, finding a way to stand out is crucial. Brand loyalty is crucial, as keeping existing customers costs significantly less than acquiring new ones. Research indicates that a 5% increase in customer retention can lead to a 25–95% increase in profits (Galo, 2014). However, measuring long-term customer loyalty can be challenging. In this study, we focus on three key metrics to comprehensively gain a clearer understanding of customer loyalty:

whether customers make repeat purchases, the frequency of these purchases, and the time interval for repurchase. If successfully adopted, VFR could offer customers a more convenient and seamless shopping experience, enhancing brand recognition. By focusing on return rates and loyalty metrics, we seek to generate statistically significant insights. These findings will not only provide practical strategies for reducing return costs but also offer valuable perspectives on building strong long-term customer relationships, eventually increasing brand competitiveness.

Research Questions, Hypotheses, and Effects

Authors: Pallavi Gudipati 50%, Yifan Ge 50%

There are two detailed research questions for this study:

1. **Compared to traditional product display methods, does the use of virtual fitting room technology help reduce the return rates of online clothing purchases over a 6-month period?**

- Null Hypothesis (H_0): $p(return)_e - p(return)_c \geq 0$

  Customers who use the virtual fitting room will not have lower return rates compared to those who do not.
- Alternative Hypothesis (H_1): $p(return)_e - p(return)_c < 0$

  Customers who use the virtual fitting room have lower return rates compared to those who do not.

2. **Compared to traditional product display methods, does the use of virtual fitting room technology increase customer loyalty, measured by repurchase rate, frequency of repurchases and hazard rate of repurchase within 6 months?**

   1. **Repurchase rate**:

      - H_0: $p(repurchase)_e - p(repurchase)_c \leq 0$

        Customers who use VFR don’t have higher repurchase rate within 6 months.
      - H_1: $p(repurchase)_e - p(repurchase)_c > 0$

        Customers who use VFR have higher repurchase rate within 6 months.

   2. **Frequency of repeated purchase**:

      - H_0: $\mu_e - \mu_c \leq 0$

        VFR doesn’t increase the frequency of customers making purchases within 6 months.
      - H_1: $\mu_e - \mu_c > 0$

        VFR increase the frequency of customers making purchases within 6 months.

   3. **Hazard rate of repurchase**:

      - H_0: $\lambda_e - \lambda_c \leq 0$

        VFR users do not make repeat purchases faster than non-VFR users.
      - H_1: $\lambda_e - \lambda_c > 0$

        VFR users make repeat purchases faster than non-VFR users.

Relative to traditional product display methods, a 10% decrease in return rates, a 10% increase in repurchase rate, 20% relative increase in repurchase frequency and a 6% increase in hazard rate respectively will be considered as a meaningful effect. When the research results show such a meaningful effect along with p value less than significant level, it means that the introduction of VFR will effectively reduce Zara’s online shopping return rate and help improve customer loyalty, which can indirectly help reduce costs and increase revenue.

Importance of the Study and Social Impact

Authors: **Pallavi Gudipati 100%**

This study emphasizes the transformative potential which VFR technology has for Zara, which offers data-driven insights to minimize the return rates and improve the customer loyalty. By leveraging AR and AI, VFR introduces a cutting-edge technological solution that redesigns the traditional retail experience. For Zara, this means improved operational efficiency, optimized resource allocation, and cost reductions. Customers benefit from a more personalized and convenient shopping experience, eliminating the need for physical trials or try-ons in finding the right fit.

Beyond organizational benefits, the implementation of VFR technology creates meaningful social and environmental impacts. It addresses the current ongoing sustainability challenges in the retail sector by significantly reducing the volume of returned items. Returned merchandise often contributes to unnecessary carbon emissions and landfill waste due to transportation and disposal inefficiencies. By minimizing these returns, Zara can actively reduce its carbon footprint and promote more sustainable retail practices.

This study also has far-reaching implications for society at large. Encouraging wider adoption of technologies like VFR can bring a cultural shift toward more eco-friendly consumer habits. For other retailers, Zara’s leadership in adopting this technology serves as a model, demonstrating how innovation can address shared challenges in the fashion industry. Competitors may follow, leading to broader improvements across the retail sector.

Additionally, the social impact extends to the access of this online retail to a large customer base. By addressing the size and fit concerns, VFR technology encourages the shoppers to embrace online shopping, making it a more inclusive and appealing option. This shift contributes to the normalization of emerging technologies in daily life, improving the technological literacy and acceptance among diverse consumer demographics.

In essence, the study not only supports Zara’s business goals but also drives meaningful societal benefits, combining economic, technological, and environmental advancements into a sustainable and impactful retail strategy.

Research Plan

Population of Interest

Authors: **Pallavi Gudipati 100%**

The population of interest for this study consists of Zara’s online customers, representing individuals who engage with the brand’s e-commerce platform to make purchases. These customers are uniquely positioned to provide valuable insights into the impact of VFR technology on user experience and purchasing behavior.

Participants must meet specific inclusion criteria to qualify for this study: they must be able to have access to Zara’s online platform. Customers who exclusively shop in physical stores or are not able to make a purchase online during the designated timeframe will be excluded, as their experiences do not align with the research objectives. By focusing on online shoppers, this study ensures that the collected data is directly relevant to assessing the efficiency and impact of VFR technology in an online shopping platform.

Sample Selection

Authors: **Pallavi Gudipati 100%**

The sample for this study will be selected from Zara’s online customer base, comprising individuals who have made purchases through Zara’s e-commerce platform. Customers who meet the inclusion criteria and consent to participate in the study will be selected through a stratified random sampling approach. This methodology accounts for diverse demographic factors such as age, location, and purchase history, ensuring a representative sample that captures varying customer preferences and behaviors.

To ensure fairness and to minimize selection bias, participants will be randomly assigned to one of two groups:

- **Experimental Group**: This group will include customers who are required to use the VFR technology during their online shopping experience.
- **Control Group**: This group will consist of customers who complete their purchases without using the VFR technology.

Such random assignment of the groups minimises the confounding variables and ensures that observed differences between the experimental and control groups are attributable to the use of VFR technology. The inclusion of these two groups allows for a comparative analysis of outcomes and ensures that both groups are representative of the broader population.

Operational Procedures

Authors: He Yang 75%, Yifan Ge 25%

This study will employ a randomized controlled trial design to evaluate the impact of VFR technology on return rates and customer loyalty. Participants will be chosen at random from among Zara's current online clientele and placed in either the experimental or control groups. Each participant will be given a personal account especially used for the experiment. The online virtual fitting room function will be available to the experimental group, and they will have to utilize it when they purchase online. Participation is entirely voluntary. In order to obtain valid and liable data and motivate customers to participate in the experiment, we will provide coupons as rewards after the experiment ends to those customers and complete at least one purchase during the trial period. Opting out at any moment won't affect the participant's relationship with Zara or their shopping experience. Participants will be advised, meanwhile, that their participation in the study may help enhance future shopping experiences for both themselves and other people.

The experimental group's participants will be given comprehensive training on how to utilize Zara's web platform's VFR function, which uses augmented reality technology to let users see how clothing might fit. The control group, on the other hand, will not have access to this function and will continue with their regular online shopping. Participants will be encouraged to shop as usual.

During the trial, all participants will get the same promotion in order to control for other outside variables. Moving forward, information on the transactions of the participants will be gathered and analyzed, such as return and repurchase rates, frequency of purchases, and time to repeat purchases. To maintain consistency, the same data gathering methods will be applied to both groups. In order to confirm the assumptions and ascertain the efficacy of VFR technology, statistical tests will be performed on the collected data in order to evaluate the variation in return rates and customer loyalty between the two groups.

The study will be conducted entirely online, and researchers will have minimal direct interaction with participants to maintain a natural shopping environment. The research team responsible for recording data will not have personal contact with participants but will rely on Zara's e-commerce data tracking system to collect the necessary information. Data collectors will be trained to ensure privacy and data accuracy, and to avoid any bias or influence on participants' shopping behaviors. Strict protocols will be in place to anonymize all data and protect participant confidentiality.

In this investigation, ethical issues are crucial. Before participating, each participant will get information about the study's objectives and the intended use of their data, and their express agreement will be sought. For the sake of participant privacy, nobody's private information will be disclosed, and data will be hidden. Participants will also be guaranteed that their involvement won't have an impact on their Zara customer status or shopping experience. Participants will be able to leave the research at any time without facing any consequences because it has been planned to reduce any possible pain or danger. The study intends to keep high ethical standards throughout its execution by guaranteeing openness, protecting privacy, and honoring the rights of participants.

Brief Schedule

Authors: He Yang 100%

The whole project will be carried out over an 8-month period.

- Week 1-2: The study design will be finalized, operational procedures will be prepared, and participants will be recruited from Zara’s online platform. The VFR system will also be developed and tested to ensure proper functionality.
- Weeks 3-4: Randomly assign participants to either the experimental or control group and provide onboarding sessions for participants using VFR technology.
- Month 2-7: The data collection phase will take place over the next 6 months, during which shopping behavior data such as return rates, repurchase frequency, and repurchase time will be collected for both groups.
- Month 8: In the last month, data analysis will be conducted to compare the return rates and customer loyalty between the two groups and validate the hypotheses. And we will compile the findings into a comprehensive report and present key results and practical recommendations to Zara.

Data Collection

Authors: **He Yang 100%**

The primary data for this study will be collected through Zara’s e-commerce platform, tracking the shopping activities of customers over a 6-month period. Throughout the six-month experiment, all participant transactions will be tracked. The data collected includes the time, amount, category of the product, and whether the product was returned for each transaction, so that we can obtain information such as the total number of transactions, return rate, number and time of repeated transactions, etc. The data points collected will include return rates, repurchase rate, frequency of repeat purchase, and time to repeat purchase. Return rates will be measured by tracking whether purchased items are returned, and the percentage of orders returned for both experimental and control groups will be analyzed. Repurchase rate will be calculated as the percentage of customers in both groups who make a second purchase within the study period. Additionally, the frequency of repeat purchases and the time interval between the initial purchase and subsequent purchases will be collected. All data will be collected automatically through Zara’s digital system to ensure accuracy, and privacy protocols will be followed to anonymize and protect customer information in accordance with data protection laws.

Data Security

Authors: **Pallavi Gudipati 100%**

Ensuring the confidentiality and security of customer data is the most important aspect in this research. To maintain privacy, all data collected from customers will be anonymized, effectively safeguarding their identities throughout the study. By removing personally identifiable information, the research ensures that sensitive details about individual participants remain private and secure.The customer transaction data will be stored in the encrypted databases, following a strict adherence to global data protection regulations or the required protocols related to the laws of privacy. The organization’s strong security systems will provide the necessary infrastructure to manage and process data securely, significantly minimizing risks of unauthorized access or breaches.

Data sharing, if required, will be strictly controlled. Only authorized personnel with proper authentication credentials will have access to the anonymized datasets, further protecting against misuse. The concept of data minimization will be strictly applied, collecting only essential information. By avoiding unnecessary collection of personal details, the research reduces both data storage demands and potential vulnerabilities.

Ethical compliance forms the foundation of this study’s approach to data security. Before collecting any information, explicit consent will be obtained from participants. Customers will be informed about the purpose of data collection, its usage, and the retention period, ensuring transparency and developing the trust. Further, researchers involved in this study will be well-trained in ethical data handling practices, holding the required certifications or badges to demonstrate their understanding of data security and research ethics.

Through these measures, the study guarantees a strong data protection while developing and maintaining a culture of transparency and accountability. These practices not only ensure compliance with ethical and legal standards but also enhance the integrity and reliability of the research outcomes.

Variables

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Outcomes (Dependent Variables)

The primary outcome will be the return rate, calculated as the percentage of returned items out of the total items they purchased, tracked through Zara's e-commerce platform, during the six-month period for each group. Customer loyalty is the other dependent variable, evaluated by three perspectives — repurchase rate, frequency of repeated purchase, and number of days after the first purchase. Repurchase rate refers to the proportion of participants who make a second purchase within the 6-month study period. The frequency of repeat purchases measures the total number of times participants make additional purchases during the study period. Time to repeat purchase will be recorded as the duration between the initial purchase and subsequent purchases. These outcomes are critical for understanding the impact of VFR technology on shopping behaviors.

Treatments (Independent Variables)

The treatment for this study is the use of VFR technology, which will be provided to the experimental group. The VFR utilizes augmented reality to allow participants to visualize how clothing items would fit them, enhancing their online shopping experience. The control group will not have access to this technology and will use the traditional product display methods. The VFR treatment will be administered through Zara's online shopping platform, where experimental participants will receive access upon logging into their accounts. The reasoning behind this treatment is that providing customers with a virtual try-on option may reduce uncertainty regarding fit and sizing, thus decreasing return rates and enhancing customer satisfaction and loyalty. The hypothesis is that customers using VFR will make more informed decisions, resulting in improved shopping outcomes.

Other Variables

In addition to the dependent and independent variables, other variables will be collected to account for factors that might affect purchasing decisions. These include demographic characteristics such as consumer age, gender, and geography, which can help explain disparities in buying habits. Product-specific characteristics, such as price and category (for example, shirts, trousers, and accessories), will also be recorded. These variables are expected to impact the likelihood of returns, as some categories may be more prone to fit issues than others. Recording these variables will help provide a more comprehensive understanding of the factors affecting customer behavior and ensure that any observed effects can be attributed to the use of VFR technology rather than external influences.

Statistical Analysis Plan

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Return Rate Analysis

To determine whether there is a statistically significant difference in return rates between the two groups, we will conduct a one-sided two-sample test of proportions. A Z-test will be employed to compare the return rates between the two groups. This test is chosen because it is well-suited for comparing proportions between two independent groups. Given that return rate is a binary categorical variable (returned or not returned), a two-sample test of proportions provides an appropriate and efficient way to assess the difference in rates across groups. Furthermore, the Z-test is robust for large sample sizes, making it a reliable method for this study, where sufficient data is expected to be collected.

The statistical significance will be evaluated using a p-value threshold of 0.05. If the p-value is less than 0.05, we will reject the null hypothesis, concluding that the Experimental group has a significantly lower return rate compared to the Control group. For this study, a 10% reduction in the return rate of the Experimental group compared to the Control group will be considered practically significant. This reduction threshold reflects the expected impact of the VFR on minimizing product returns.

Additionally, we also explore relationships between other variables with the likelihood of returns, such as customer gender, age, and product price. Since the return status is a categorical variable, we will construct a logistic regression model. This approach will allow us to assess the impact of each variable on the likelihood of a return.

Customer Loyalty Analysis

Customer loyalty is examined through three dimensions: repurchase rate, repurchase frequency, and hazard rate of repurchase.

1. **Repurchase Rate**

The analysis of repurchase rate is similar to that of the return rate. We will conduct a one-sided two-sample test of proportions to determine whether there is a significant difference in repurchase rates between the Experimental and Control groups.

2. **Repurchase Frequency**

Repurchase frequency refers to the total number of repeat purchases made by a customer over the observation period. This variable provides insight into the depth of customer engagement. Repurchase frequency is a count variable representing non-negative integers. Given the nature of this variable, Poisson regression is selected as the appropriate method to model repurchase frequency. Poisson regression is ideal for count data that is non-negative and sparsely distributed, as it assumes that the mean and variance of the outcome are equal. Additionally, this method allows us to quantify the relationship between experimental conditions (e.g., VFR usage) and the frequency of repeat purchases while controlling for covariates such as gender, age, and income. By analyzing repurchase frequency, we aim to determine whether customers in the Experimental group exhibit a significantly higher number of repeat purchases compared to the Control group.

3. **Hazard Rate of Repurchase**

The hazard rate of repurchase represents the likelihood of a customer making a repeat purchase at a specific point in time, given that they have not already done so. It captures how quickly customers are likely to make repeat purchases over time.

We utilize the collected data to calculate the time interval from the first purchase to the first repeat purchase for each customer. This time-to-event data is then analyzed using Cox Proportional Hazards Regression, which is a robust method for examining the effect of covariates on the timing of repeat purchases. Cox regression is chosen because it does not assume a specific distribution for the time-to-event data, making it highly flexible and suitable for analyzing customer behavior. The model provides a hazard ratio (HR), which quantifies the relative likelihood of repeat purchases for the Experimental group compared to the Control group. A hazard ratio greater than 1 indicates that the Experimental group repurchases faster than the Control group.

To complement the regression analysis, we employ Kaplan-Meier survival curves to visually estimate and compare the time-to-repurchase distributions between the two groups. The survival curves not only provide a clear visualization of the differences but also reinforce the conclusions drawn from the Cox model.

Sample Size and Statistical Power

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In this study, the sample size is determined based on statistical power considerations to ensure reliable results. We aim to detect a 10% decrease in return rates (from 30% to 20%) as the primary outcome, which is a key metric for evaluating the impact of virtual fitting room technology on return behavior. The effect size is set at this 10% reduction, with a significance level of 0.05 and a desired statistical power of 0.7, which is a commonly accepted threshold for ensuring the robustness of the findings.

Using these parameters, we calculate the minimum required sample size to achieve the suggested effect size. The result of this calculation indicates that a sample size of 175 participants per group is necessary. However, to account for potential challenges such as participant attrition, measurement errors, or other practical issues, we opt to recruit 200 participants per group. This number not only ensures that the study maintains statistical power but also remains feasible within the available resources and time constraints.

By selecting 200 participants per group, we strike a balance between statistical rigor and practical feasibility, ensuring that the study has sufficient power to detect meaningful effects while also being logistically manageable. This approach provides confidence that the experiment will yield reliable and actionable insights, contributing to a more informed evaluation of the impact of virtual fitting room technology on return rates.

Possible Recommendations

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Research Question 1: Return Rate

a. Null Hypothesis is Not Rejected

It indicates that the virtual fitting room does not significantly reduce return rates. In this case, we would recommend evaluating the technology itself to identify potential improvements in accuracy or usability that could enhance its effectiveness. Additionally, alternative strategies, such as better product descriptions or customer support, could be explored to address high return rates. Further studies might focus on specific customer segments to determine if VFR has a more pronounced effect on certain groups.

b. Null Hypothesis is Rejected

It means the VFR significantly reduces return rates. The recommendation would be to integrate the VFR into the company's online shopping platform as a key feature. This could be paired with marketing efforts to highlight its benefits in reducing returns. Additionally, the company could monitor long-term trends to ensure the technology continues to deliver value over time.

Research Question 2: Customer Loyalty

a. Null Hypothesis is Not Rejected

It suggests that the VFR does not significantly improve customer loyalty, as measured by metrics such as repeat purchase rate, frequency, or time to first repeat purchase. In this case, we would recommend further investigation into why the VFR is not driving loyalty. Possible areas of focus include identifying barriers to adoption, understanding customer perceptions of the VFR, or integrating the VFR with loyalty programs or incentives to encourage repeat purchases.

b. Null Hypothesis is Rejected

It indicates that the VFR significantly improves customer loyalty. The recommendation would be to expand its use across the platform and highlight its positive impact in customer communications and promotional efforts. This could also include optimizing the technology to further enhance the customer experience, ensuring its long-term success in fostering loyalty and repeat purchases.

Limitations and Uncertainties

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Firstly, due to practical considerations and constraints in time and resources, the experiment measures outcomes over a six-month period. While this provides valuable short-term insights, it may not fully capture the long-term effects of VFR on customer loyalty and repeat purchase behavior. This limitation restricts our ability to understand sustained behavioral changes. Additionally, clothing purchases are highly seasonal, and a six-month timeframe cannot encompass all seasonal variations within a full year, potentially overlooking trends specific to different times of the year.

Secondly, because the experimental design cannot completely blind participants to the study's purpose, they are aware that the focus is on evaluating the impact of VFR. This awareness may introduce subjective biases, as participants might consciously or unconsciously alter their behavior to align with perceived expectations, potentially skewing the results. Additionally, although we require participants in the experimental group to use the VFR technology during their purchases throughout the experiment, we are unable to monitor whether they genuinely and adequately utilize this technology during their shopping experience.

Lastly, real-world clothing purchase behavior is influenced by a variety of external factors that are not fully accounted for in the experiment. For example, prior online shopping experience, individual product preferences, or cultural attitudes toward returns could significantly affect customer decisions. These unmeasured variables may introduce confounding effects, making it difficult to isolate the true impact of VFR.

While our experiment provides a clear and direct comparison that demonstrates the impact of virtual fitting room technology on return rates and customer loyalty, applying these findings to real-world scenarios requires greater prudence. The controlled experimental setting may not fully capture the complexities and variability of real-world applications, and additional studies may be needed to validate the results in more diverse and practical contexts.

Part 2: Simulated Studies

Authors: Yifan Ge 50%, Zhifeng Wu 50%

We employed simulation technology to better evaluate our research plan. Each research question will be simulated under two scenarios:

- Scenario 1: The virtual fitting room (VFR) has no impact on the variables under investigation.
- Scenario 2: An expected effect is observed.

Initially, we will conduct single simulations for each research question to verify the validity of the experimental design, ensuring there are no logical errors in hypotheses, variable settings, or sample distributions. This step will also confirm whether the statistical tests can detect the expected effects. Subsequently, we will perform repeated simulations for all research questions to assess the stability of the results and evaluate the probabilities of Type I and Type II errors. Simulations allow us to test experimental designs in a virtual environment, minimizing the waste of time, budget, and resources during actual experiments. They also help identify potential issues in the experimental design, prompting us to refine specific details and make necessary improvements.

For the simulated experiments, we made some general assumptions about customers and transaction data applicable to all research questions:

1. Considering the typical customer demographics of online clothing brands, we assume the gender ratio of participants is 60% female to 40% male.
2. Age: Mean = 35, Standard Deviation = 10, following a normal distribution.
3. Income: Mean = $50,000, Standard Deviation = $15,000, following a normal distribution.
4. Product categories: Transactions are distributed among three categories with the following proportions: “Tops” = 50%, “Bottoms” = 30%, “Accessories” = 20%.
5. Product prices by category: “Tops”: Mean = $80, SD = $30; “Bottoms”: Mean = $60, SD = $15; “Accessories”: Range = $20–$80.

Research Question 1:

Regarding the return rate, we assume that the probability of returns is lower for male customers, older customers, and lower-priced products.

Specifically, we assume the following factors influence the return rate:

1. The baseline return rate is 30%.
2. In scenario 2, the use of VFR reduces the return rate by 10%.
3. Male customers have a return rate that is 5% lower than female customers.
4. For every additional year of age, the return rate decreases by 0.2%.
5. For every one-unit increase in product price, the return rate increases by 0.2%.

Following simulation will calculate the return probability for each customer based on our assumption, then simulate whether each customer returns the product using the calculated probabilities. Two sample Tests of Proportion will be used in this case, and Logistic Regression will be used in analyzing other variables.

Scenario 1: No Effect

Authors: Yifan Ge 50% and Zhifeng Wu 50%

Simulation

```
# calculate reutrn probabilities
data1_no$return_prob_no_effect <- baseline_return_rate +
    ifelse(data1_no$gender == "Male", gender_effect, 0) +
    data1_no$age * age_effect + data1_no$price * price_effect
data1_no$return_prob_no_effect <- pmin(pmax(data1_no$return_prob_no_effect,
    0), 1)
# simulation return or not
data1_no$return_no_effect <- rbinom(nrow(data1_no), 1, data1_no$return_prob_no_effect)
```

Analysis

```
P-value: 0.8164
```

```
95% Confidence Interval: [-0.08941, 1]
```

```
Sample Estimates (Control, Experimental): 0.31017 , 0.34257
```

The 2 samples Test of Proportion results show that the p-value is 0.8164, greater than 0.05, meaning we cannot reject the null hypothesis. There is insufficient evidence to suggest a significant difference in return rates between the Control and Experimental groups. Therefore, the use of the virtual fitting room does not appear to reduce the return rate.

Scenario 2: An Expected Effect

Authors: Yifan Ge 50%, Zhifeng Wu 50%:

Simulation

```
# calculate reutrn probabilities
data1_effect$return_prob <- baseline_return_rate + ifelse(data1_effect$group ==
    "Experimental", vfr_effect, 0) + ifelse(data1_effect$gender ==
    "Male", gender_effect, 0) + data1_effect$age * age_effect +
    data1_effect$price * price_effect
data1_effect$return_prob <- pmin(pmax(data1_effect$return_prob,
    0), 1)
# simulation return or not
data1_effect$return <- rbinom(nrow(data1_effect), 1, data1_effect$return_prob)
```

Analysis

```
P-value: 0.00028
```

```
95% Confidence Interval: [0.05842, 1]
```

```
Sample Estimates (Control, Experimental): 0.34491 , 0.23174
```

The test results show a p-value of less than 0.05, leading to the rejection of the null hypothesis. This indicates that the return rate in the Experimental group is significantly lower than that in the Control group, supporting the hypothesis that VFR effectively reduces return rates.

Moreover, the 95% confidence interval for the difference in return rates is [0.0584, 1.0000]. The lower bound of 0.0345 suggests that the return rate in the Experimental group is at least 5.84% lower than that in the Control group. The estimated proportions show that the return rate for the Control group is 34.49% and for the Experimental group is 23.17%. The effect size of 10% is satisfied, highlighting a significant reduction in the return rate for the use of VFR.

Analysis of other variables

Since the return status is a binary variable, a logistic regression model can be used to analyze the relationship between relevant factors and the likelihood of returns. The results reveal that gender and age are not significant in either scenario, suggesting that their impact on the return rate is minimal. In contrast, price is significant in both scenarios, indicating that higher-priced products are more likely to be returned.

Research Question 2:

Research Question 2 focuses on repeat purchases, aiming to quantify customer loyalty from three perspectives: **Research Question 2.1** (repeat purchase rate), **Research Question 2.2** (number of repeat purchases), and **Research Question 2.3** (time to first repeat purchase).

Regarding repeat purchases, we hypothesize that female customers and younger individuals are more likely to make repeat purchases.

Research Question 2.1

To investigate whether the use of the virtual fitting room helps improve the repeat purchase rate, we adopted the same approach as in Research Question 1, using a two-sample proportion test for analysis.

Specifically, we assume the following factors influence the repeat purchase rate:

1. The baseline repeat purchase rate is 50%.
2. In scenario 2, the use of the virtual fitting room (VFR) increases the repeat purchase rate by 10%.
3. Female customers have a repeat purchase rate that is 5% higher than male customers.
4. For every additional year of age, the repeat purchase rate decreases by 0.2%.

Scenario 1: No Effect

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
# calculate probability
data2.1_no$purchase_prob_no_effect = baseline_rate + ifelse(data2.1_no$gender ==
    "Female", gender_effect, 0) + data2.1_no$age * age_effect
data2.1_no$purchase_prob_no_effect = pmin(pmax(data2.1_no$purchase_prob_no_effect,
    0), 1)

# stimulation, 0 means first purchase, 1 means
# repurchase
set.seed(123)
data2.1_no$repurchase_no_effect <- rbinom(nrow(data2.1_no),
    1, data2.1_no$purchase_prob_no_effect)
```

Analysis

```
P-value: 0.5
```

```
95% Confidence Interval: [-1, 0.08219]
```

```
Sample Estimates (Control, Experimental): 0.515 , 0.52
```

p value is greater than 0.05, meaning that there is insufficient evidence to suggest a significant difference in repurchase rates between the Control and Experimental groups. Therefore, the use of the virtual fitting room does not appear to reduce the repurchase rate.

Scenario 2: An Expected Effect

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
data2.1_effect$purchase_prob_effect = baseline_rate + ifelse(data2.1_effect$group ==
    "Experimental", vfr_effect, 0) + ifelse(data2.1_effect$gender ==
    "Female", gender_effect, 0) + data2.1_effect$age * age_effect
data2.1_effect$purchase_prob_effect = pmin(pmax(data2.1_effect$purchase_prob_effect,
    0), 1)

set.seed(123)
data2.1_effect$repurchase <- rbinom(nrow(data2.1_effect),
    1, data2.1_effect$purchase_prob_effect)
```

Analysis

```
P-value: 0.02177
```

```
95% Confidence Interval: [-1, -0.01897]
```

```
Sample Estimates (Control, Experimental): 0.515 , 0.62
```

The 2-sample proportion test shows a significant difference between the Control group (51.5%) and the Experimental group (62%) with a p-value of 0.02177. This supports the hypothesis that the Experimental group has a higher repurchase rate.

Analysis of other variables

Similar to Research Question 1, since repeat purchase behavior is a binary variable, a logistic regression model is used to analyze the relationship between relevant factors and the likelihood of repeat purchases. The results indicate that gender and age are not significant in either scenario, suggesting that their impact on the probability of repeat purchases is minimal.

Research Question 2.2

Investigating the impact of virtual fitting room technology on users' repeat purchase frequency. A Poisson distribution will be used, specialized to describe discrete counts (frequency of purchase) at a fixed time.

Specifically, we assume the following factors influence the purchase frequency:

1. Baseline purchasing frequency is 2. In Scenario 2, purchasing frequency using VFR increase to 2.4.
2. High-income group (income > 60,000) and purchased Accessories to increase the repeat purchase rate by 1.5 times.

Scenario 1: No Effect

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
set.seed(123)
data2.2_scenario1 <- generate_purchase_counts(data2.2_scenario1,
    lambda_control = 2, lambda_experimental = 2)
```

Analysis

```
Poisson Regression Coefficients:
```

```
 - (Intercept) : Estimate = 0.8029 , P-value = 0
 - groupExperimental : Estimate = 5e-04 , P-value = 0.9914
 - genderMale : Estimate = -0.1211 , P-value = 0.0183
 - age : Estimate = 1e-04 , P-value = 0.9604
 - income : Estimate = 0 , P-value = 0.0939
 - categoryBottom : Estimate = -0.1907 , P-value = 0.0066
 - categoryTop : Estimate = -0.1884 , P-value = 0.0062
 - price : Estimate = -5e-04 , P-value = 0.6192
```

```
Risk Ratio (Scenario 1): 1.0005
```

The Poisson regression results indicate no significant difference in purchase counts between the Experimental and Control groups (p=0.99, RR=1.0005) . Additionally, other variables such as gender, age, income and price show no significant impact on purchase counts, suggesting limited explanatory power of the model. Category seems related to purchase counts here.

Scenario 2: An Expected Effect

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
set.seed(123)
data2.2_scenario2 <- generate_purchase_counts(data2.2_scenario2,
    lambda_control = 2, lambda_experimental = 2.4)
```

Analysis

```
Poisson Regression Coefficients:
```

```
 - (Intercept) : Estimate = 0.7866 , P-value = 0
 - groupExperimental : Estimate = 0.1773 , P-value = 2e-04
 - genderMale : Estimate = -0.1414 , P-value = 0.004
 - age : Estimate = 3e-04 , P-value = 0.892
 - income : Estimate = 0 , P-value = 0.0931
 - categoryBottom : Estimate = -0.1716 , P-value = 0.0103
 - categoryTop : Estimate = -0.2027 , P-value = 0.0021
 - price : Estimate = -1e-04 , P-value = 0.893
```

```
Risk Ratio (Scenario 1): 1.194
```

The result shows that the Experimental group has a significantly higher purchase count compared to the Control group ($p<0.05$). Meanwhile, the risk ratio is 1.19, which indicates the experimental group's purchase frequency is 1.19 times higher than that of the control group, a 19.4% improvement.

Research Question 2.3

Survival curves will be used to analyze the impact of VFR on the time to repurchases by customers, to explore whether the use of VFR causes customers to make repurchases earlier. Consequently generate Kaplan-Meier survival curves to visualize the differences.

Specifically, we assume the following factors influence the time interval for repurchase:

1. Base hazard rate for repurchase is 0.1. In Scenario 2, the hazard rate using VFR is increased to 0.16.
2. Female repeat purchase rates are 1.2 times higher than male; young people (age<30) repurchase at 1.3 times the rate of other ages.

Scenario 1: No Effect

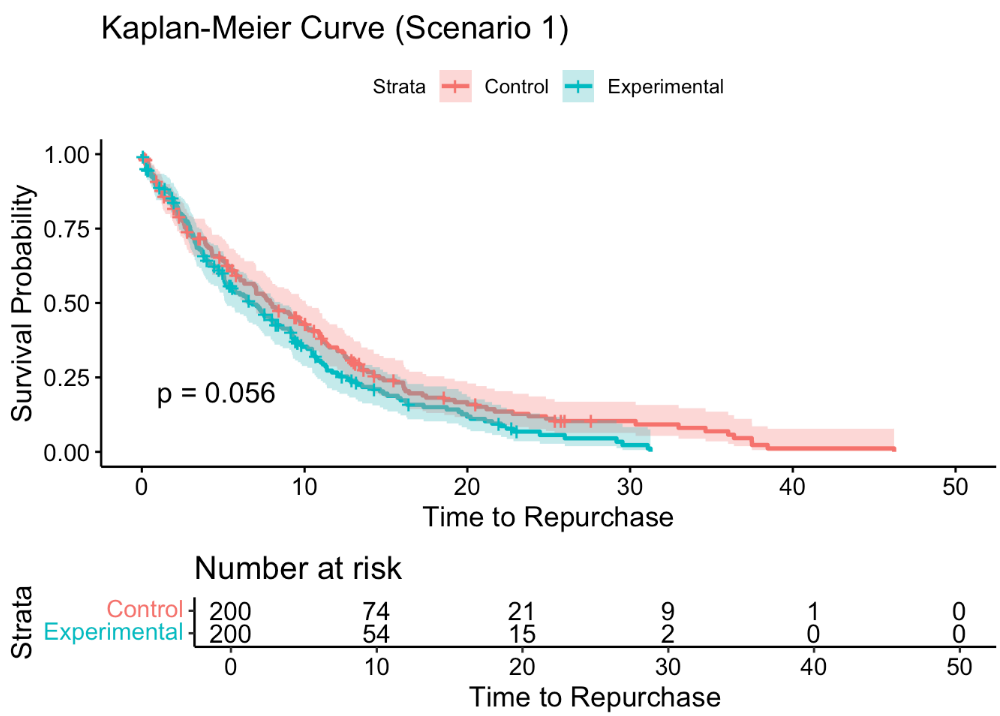
Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
# generate survival time for each customer (adjust
# hazard rate)
set.seed(123)
data2.3_scenario1[, time_to_repurchase_case1 := mapply(function(gender,
    age) {
    group_rate <- base_rate_control
    rexp(1, rate = adjusted_rate(gender, age, group_rate))
}, gender = gender, age = age)]

# 80% participants repurchased during 6 months
data2.3_scenario1[, status_case1 := sample(c(1, 0), size = .N,
    replace = TRUE, prob = c(0.8, 0.2))]
```

Analysis




```
Hazard Ratio (HR): 1.2394
```

```
P-value: 0.0562
```

```
Log-rank Test P-value: 0.0561
```

```
95% Confidence Interval: [ 0.9944 ,  1.5447 ]
```

In Scenario 1, the Cox regression showed that the risk of repeat purchases was 23.9% higher in the experimental group than in the control group (HR = 1.239), but not significant (p = 0.056). Also the confidence interval [0.9944, 1.545] contains 1 ,and the model is weakly discriminatory (Concordance = 0.517).

In the no effect scenario, the survival curves of the two groups almost overlapped, indicating that the difference between the two groups in terms of time to repeat purchase was small. And the Log-rank test has a p-value of 0.06, which shows that this difference is not statistically significant.

Scenario 2: An Expected Effect

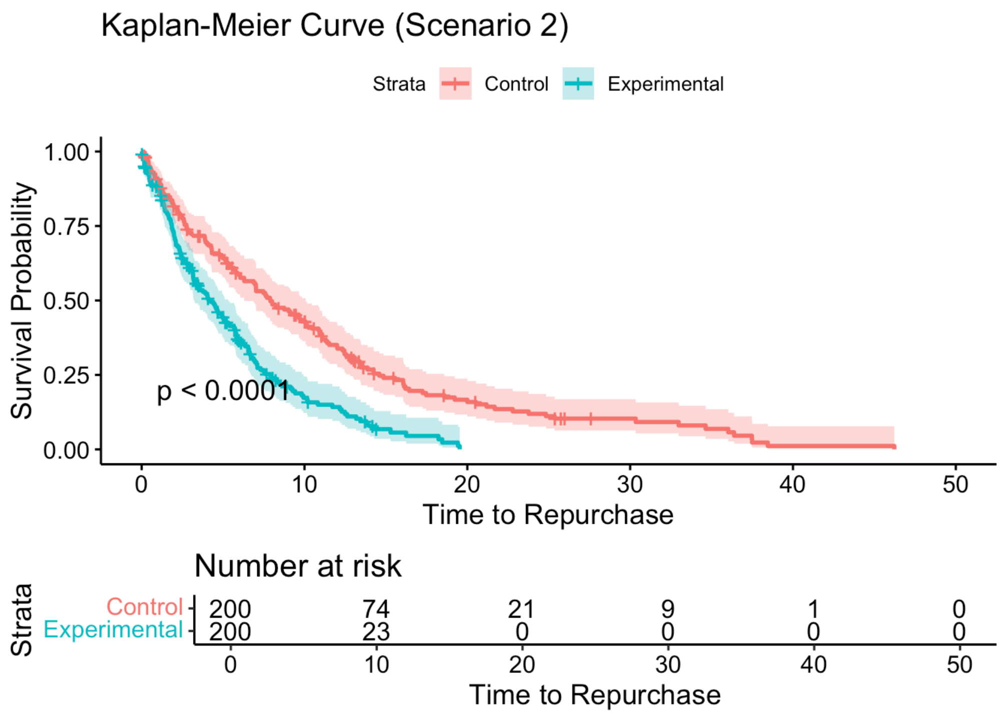
Authors: Yifan Ge 50%, Zhifeng Wu 50%

Simulation

```
set.seed(123)
data2.3_scenario2[, time_to_repurchase_case2 := mapply(function(gender,
    age, group) {
    group_rate <- ifelse(group == "Experimental", base_rate_experimental,
        base_rate_control)
    rexp(1, rate = adjusted_rate(gender, age, group_rate))
}, gender = gender, age = age, group = group)]

data2.3_scenario2[, status_case2 := sample(c(1, 0), size = .N,
    replace = TRUE, prob = c(0.8, 0.2))]
```

Analysis




```
Cox Proportional Hazards Model Results:
```

```
Hazard Ratios (HR):
```

```
 - groupExperimental : HR = 1.9218 , P-value = 0 , 95% CI = [ 1.5262 , 2.42 ]
 - genderMale : HR = 0.7327 , P-value = 0.0065 , 95% CI = [ 0.5858 , 0.9165 ]
 - age : HR = 0.9857 , P-value = 0.0123 , 95% CI = [ 0.9746 , 0.9969 ]
```

```

Log-rank Test P-value: 0
```

The Cox regression results show that the Experimental group significantly accelerates repeat purchases, with a hazard ratio of 1.92, indicating a 92% higher risk of repeat purchases compared to the Control group. Male customers have a lower hazard ratio, suggesting they are 27% less likely to make repeat purchases compared to females. Age also has a slight but significant negative effect, with older customers showing a marginally lower likelihood of repeat purchases.

In this scenario, the survival curve of the experimental group is significantly lower than the control group, showing that the customers in the experimental group completed their repeat purchases in a shorter time. Meanwhile, the Log-rank test shows there is a statistical significance between two groups.

Repeat simulation

Authors: Yifan Ge 50%, Zhifeng Wu 50%

Given the randomness inherent in single simulation results, we conducted 1,000 repeated simulations for each research question to assess the reliability of the outcomes. The table below summarizes the results of the repeated simulations across different research questions and scenarios.

Research Question	Scenario	Mean Effect in Simulated Data	95% Confidence Interval of Mean Effect	Percentage of False Positives	Percentage of True Negatives	Percentage of False Negatives	Percentage of True Positives
Question 1	No Effect	0.002340	[-0.080125, 0.090000]	0.027	0.973	NA	NA
Question 1	Effect: 10% decrease	-0.100100	[-0.18, -0.02]	NA	NA	0.287	0.713
Question 2.1	No Effect	0.004510	[-0.095000, 0.100125]	0.056	0.944	NA	NA
Question 2.1	Effect: 10% increase	0.102600	[0, 0.195]	NA	NA	0.378	0.622
Question 2.2	No Effect	0.003045	[-0.245, 0.255]	0.034	0.966	NA	NA
Question 2.2	Effect: 20% related increase/ 0.4 increase in frequency	0.400590	[0.09, 0.690125]	NA	NA	0.217	0.783
Question 2.3	No Effect	1.003208	[0.8161075, 1.2266927]	0.521	0.479	NA	NA
Question 2.3	Effect: 60% related increase/ 0.06 increase in rate	1.605389	[1.292141, 1.963707]	NA	NA	1.000	0.000

In the simulations of the 4 Research Questions, the model has good detection ability when the effects are large. However, it was insufficient with small effects or highly noisy data. In Research Question 1, the model judged accurately when there was no effect and the false positive rate was low; when the effect was decreased by 10%, there was a significant negative effect, but the false negative rate was 28.7%. In Research Question 2.1, a 10% increase in effect showed a significant positive effect, but the false negative rate was similarly high (37.8%). In Research Question 2.2, an increase in frequency of 0.4 was significant with a slightly lower false negative rate (21.7%). In Research Question 2.3, the model performed completely accurately with no false positives or false negatives when the effect was increased by 60%.

By analyzing relevant indicators, the false positive rate is usually lower in the no effect scenario, which means that the model judges accurately in the no effect scenario; in the scenario with effect, the true positive rate of the model is generally higher, among which the results of Question 2.3 and Question 2.2 are the most desirable (96.1% and 78.3%). There are also some issues, like the false-negative rate is higher in scenarios with small effects, such as 37.8% in Question 2.1, which suggests that the model ignores the true effects under conditions of large simulation noise and small effects.

In conclusion, this research will offer reliable, data-driven insights, and the findings can serve as a solid foundation for Zara to make informed decisions about implementing VFR technology.

References:

Authors: all members

1. Biron, B. (n.d.). Retailers like Macy's, Adidas, and modcloth are turning to virtual fitting rooms to let consumers "try on" clothing before buying it online. Business Insider. https://www.businessinsider.com/retailers-like-macys-adidas-are-turning-to-virtual-fitting-rooms-2020-8 (https://www.businessinsider.com/retailers-like-macys-adidas-are-turning-to-virtual-fitting-rooms-2020-8)
2. Buehler, T. L. (2024, July 15). The virtual fitting room: Revolutionizing Apparel Shopping: American Military University (AMU). AMU. https://www.amu.apus.edu/area-of-study/business-administration-and-management/resources/the-virtual-fitting-room/ (https://www.amu.apus.edu/area-of-study/business-administration-and-management/resources/the-virtual-fitting-room/)
3. Chan, A. (2023, April 6). The true cost of apparel returns: Alarming return rates require loss-minimization solutions. *Coresight Research*. https://coresight.com/research/the-true-cost-of-apparel-returns-alarming-return-rates-require-loss-minimization-solutions/#:~:text=One%20estimate%20from%20Optoro%2C%20a,in%202023%2C%20excluding%20merchandise%20waste (https://coresight.com/research/the-true-cost-of-apparel-returns-alarming-return-rates-require-loss-minimization-solutions/#:~:text=One%20estimate%20from%20Optoro%2C%20a,in%202023%2C%20excluding%20merchandise%20waste
4. Constable, H. (n.d.). Your brand new returns end up in landfill. *BBC Earth*. https://www.bbcearth.com/news/your-brand-new-returns-end-up-in-landfill (https://www.bbcearth.com/news/your-brand-new-returns-end-up-in-landfill)
5. Gallo, A. (2014, November 5). The value of keeping the right customers. Harvard Business Review. https://hbr.org/2014/10/the-value-of-keeping-the-right-customers (https://hbr.org/2014/10/the-value-of-keeping-the-right-customers)
6. Daroch, B., Nagrath, G., & Gupta, A. (2021). A study on factors limiting online shopping behaviour of consumers. *Rajagiri Management Journal, 15*(1), 39–52. https://doi.org/10.1108/ramj-07-2020-0038 (https://doi.org/10.1108/ramj-07-2020-0038)
7. Fadilah Haya, K., Afina, H., & Ismi, D. (2024). The contribution of virtual fitting room in fashion clothing business: A systematic literature review. *International Journal of Economics, Business and Accounting (InJEBA)*. https://doi.org/10.5281/zenodo.12577578 (https://doi.org/10.5281/zenodo.12577578)
8. Fokina, M. (2024, September 20). Online shopping statistics: Ecommerce trends for 2024. *Tidio*. https://www.tidio.com/blog/online-shopping-statistics/ (https://www.tidio.com/blog/online-shopping-statistics/)
9. Forbes Technology Council. (2023, November 28). Is it time to invest in a virtual fitting room? *Forbes*. https://www.forbes.com/councils/forbestechcouncil/2023/11/28/is-it-time-to-invest-in-a-virtual-fitting-room/ (https://www.forbes.com/councils/forbestechcouncil/2023/11/28/is-it-time-to-invest-in-a-virtual-fitting-room/)
10. Grand View Research. (n.d.). Virtual fitting room market size, share & trends analysis report. *Grand View Research*. https://www.grandviewresearch.com/industry-analysis/virtual-fitting-room-market (https://www.grandviewresearch.com/industry-analysis/virtual-fitting-room-market)
11. Jaya Prabha, R., & Karunanidhi, M. (2019). A study on consumers problems towards online shopping. *International Journal of Business and Management Invention*, 26–28. https://www.ijbmi.org/papers/Special%20Issue/NCETIDM-2017/F2628.pdf (https://www.ijbmi.org/papers/Special%20Issue/NCETIDM-2017/F2628.pdf)
12. Liu, Y., Liu, Y., Xu, S., Cheng, K., Masuko, S., & Tanaka, J. (2020). Comparing VR- and AR-based try-on systems using personalized avatars. *Electronics, 9*(11), 1814. https://doi.org/10.3390/electronics9111814 (https://doi.org/10.3390/electronics9111814)
13. McCarthy, D., McDonald, J., & Maake, K. (2021, November 9). Your guide to virtual fitting rooms. *Tech Brew*. https://www.emergingtechbrew.com/guides/your-guide-to-virtual-fitting-rooms (https://www.emergingtechbrew.com/guides/your-guide-to-virtual-fitting-rooms)
14. Sun, L., Lyu, G., Yu, Y., & Teo, C. P. (2020). Cross-border e-commerce data set: Choosing the right fulfillment option. *Manufacturing & Service Operations Management, 23*(5), 1297–1313. https://doi.org/10.1287/msom.2020.0887 (https://doi.org/10.1287/msom.2020.0887)
15. Tait, A. (2023, March 31). Buy. Return. Repeat … What really happens when we send back unwanted clothes? *The Guardian*. https://www.theguardian.com/global-development/2023/mar/31/what-happens-when-we-send-back-unwanted-clothes (https://www.theguardian.com/global-development/2023/mar/31/what-happens-when-we-send-

back-unwanted-clothes)

16. Xiong, G. (2023, January 18). Virtual fitting room effect: Moderating role of body mass index. *Syracuse University Whitman School of Management*. https://whitman.syracuse.edu/faculty-and-research/2023/01/18/virtual-fitting-room-effect-moderating-role-of-body-mass-index (https://whitman.syracuse.edu/faculty-and-research/2023/01/18/virtual-fitting-room-effect-moderating-role-of-body-mass-index)

17. Zheng, S. (2023, April 6). The true cost of apparel returns: Alarming return rates require loss-minimization solutions. *Coresight Research*. https://coresight.com/research/the-true-cost-of-apparel-returns-alarming-return-rates-require-loss-minimization-solutions/#:~:text=One%20estimate%20from%20Optoro%2C%20a,in%202023%2C%20excluding%20merchandise%20waste (https://coresight.com/research/the-true-cost-of-apparel-returns-alarming-return-rates-require-loss-minimization-solutions/#:~:text=One%20estimate%20from%20Optoro%2C%20a,in%202023%2C%20excluding%20merchandise%20waste

Appendix

Code for calculate sample size

```
library(pwr)
sample.size.p <- pwr.2p.test(h = ES.h(p1 = 0.3, p2 = 0.2),
    sig.level = 0.05, power = 0.7, alternative = "greater")
ceiling(sample.size.p$n)
```

```
[1] 175
```

Full code for repeat simulation

```
# load library and function
library(data.table)
library(DT)
analyze.experiment <- function(the.dat, type = "t.test",
    iv.name, dv.name, value.treatment, value.control, alternative = "two.sided",
    alpha = 0.05) {
    require(data.table)
    setDT(the.dat)

    if (type == "t.test") {
        the.test <- t.test(x = the.dat[get(iv.name) == value.treatment,
            get(dv.name)], y = the.dat[get(iv.name) == value.control,
            get(dv.name)], alternative = alternative, conf.level = 1 -
            alpha)
    }
```