SOFTWARE AS A SERVICE (SAAS) LIFETIME DEALS: CONSUMER PREFERENCES AND PURCHASE INTENTIONS

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ETHICAL DECLARATION

I hereby declare that I am the sole author of this thesis and that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

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ABSTRACT

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Most startups, especially in the competitive SaaS market, face significant financial challenges and regrettably, many fail within their first year. Herein, lifetime deals emerge as a promising strategy that provides upfront revenue, secures a user base, and enables competition against established brands. However, such deals come with their own benefits (receiving the service for a lifetime) and risks (committing money upfront) for consumers. Understanding the factors that affect consumer purchase intentions in lifetime deals is crucial for maximizing these benefits and mitigating the risks. This research aims to understand the factors affecting consumer purchase intentions for SaaS lifetime deals by examining the key SaaS lifetime attributes (price, human support, refund option, regular feature updates) and consumer-related variables (perceived risk, trust, digital competency, usage frequency, and period). Employing diverse methodologies, including focus group study, choice-based conjoint analysis, hierarchical Bayesian model, confirmative factor analysis (CFA), and factor score regression method, this research analyzes responses from 2195 participants. Findings show that all key SaaS lifetime attributes significantly affect consumer utility. Also, consumer-related variables such as usage period, frequency, perceived trust, and digital competency positively affect purchase intention. Certain moderating effects are observed, including the utility of price on perceived risk, and feature updates on usage frequency. The research advances the theoretical understanding of consumer behavior in SaaS, especially lifetime deals while providing startups with a valuable model to navigate challenges and make strategic decisions for long-term success.

Keywords: Software as a Service (SaaS), Startup, Lifetime Deal, Conjoint Analysis, Purchase Intention, Hierarchical Bayesian Model.

ÖZET

HİZMET OLARAK YAZILIMIN ÖMÜR BOYU SUNULMASI: TÜKETİCİLERİN TERCİHLERİ VE SATIN ALMA NİYETLERİ

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Özellikle rekabetçi SaaS pazarında olan çoğu girişim, henüz bir yılını doldurmadan finansal problemler nedeniyle kapanmaktadır. Bu noktada ömür boyu teklifler, yeni girişimlerin operasyonel maliyetlerini sürdürebilecek gelir elde etmesini, kullanıcı kitlesi elde etmesini ve rekabetçi konuma gelmesini sağlamaktadır. Öte yandan, ömür boyu teklifler tüketicilere fayda (hizmeti ömür boyu kullanmak) ve riskleriyle (tek seferde önden ödeme yapmak) beraber gelmektedir. Dolayısıyla kullanıcıların satın alma niyetlerini etkileyecek hizmet özelliklerini anlamak büyük önem taşımaktadır. Bu araştırma, ana SaaS ömür boyu özelliklerini (fiyat, insan desteği, iade seçeneği, düzenli özellik güncellemeleri) ve tüketiciye ilişkin değişkenleri (algılanan risk, güven, dijital yeterlilik, kullanım sıklığı ve dönemi) inceleyerek, SaaS ömür boyu anlaşmalar için tüketici satın alma niyetlerini etkileyen faktörleri anlamayı amaçlamaktadır. Bu araştırmada, odak grup çalışması, seçime dayalı konjoint analizi, hiyerarşik Bayesci model, doğrulayıcı faktör analizi (CFA) ve faktör skor regresyon yöntemi gibi çeşitli yöntemler kullanarak, 2195 katılımcıdan gelen yanıtlar analiz edilmiştir. Bulgular, tüm belirlenen önemli SaaS ömür boyu özelliklerinin tüketicilerin algıladığı faydayı anlamlı olarak etkilediğini göstermektedir. Ayrıca, kullanım dönemi sıklığı, algılanan güven ve dijital yeterlilik gibi tüketiciye ilişkin değişkenler de satın alma niyetini olumlu yönde etkilemektedir. Algılanan risk üzerinde fiyatın, kullanım sıklığı üzerinde özellik güncellemelerinin faydası gibi belirli düzenleyici etkiler gözlemlenmiştir. Bu araştırma, SaaS ömür boyu teklif kapsamındaki tüketici davranışlarını araştırarak teorik katkı sunmanın yanı sıra, yeni girişimlerin finansal zorlukları aşabilmek için ömür boyu teklifleri nasıl kullanabileceğine dair bir çerçeve sunmaktadır.

Anahtar Kelimeler: Hizmet Olarak Yazılım (SaaS), Girişim, Ömür Boyu Anlaşma, Konjoint Analizi, Satın Alma Niyeti, Hiyerarşik Bayes Analizi.

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CHAPTER 1: INTRODUCTION

The way services are provided and consumed has seen remarkable transformation. Historically, services, characterized as intangible activities or benefits that cannot be owned and which are produced and consumed simultaneously with the service provider, often directly interacting with the consumer in the course of delivery, have spanned a range of sectors, including hospitality, banking, and healthcare (Zeithaml et al., 1985). Such characteristics differentiate services from goods and present unique challenges for service providers in terms of design, marketing, and delivery. This traditional service landscape began to evolve with the advent of digital technologies. In this digital era, the service concept has experienced a fundamental shift (Yoo et al., 2012). Services began to be increasingly digitized, leading to a transformation in their delivery and consumption. Consumers began purchasing individual software products for installation on their personal or business computers (Cusumano et al., 2014).

Yet, with the changing business ecosystem, this idea of "software being a product" has started to change into "software being a service". Now this phenomenon is called Software as a Service (SaaS), which is one of the fastest-growing industry in technology at the moment (Global SaaS Market Size, Share, Growth Analysis report, 2023). Software as a Service (SaaS) can be defined as a model where the software is shared on the internet where anyone that needs it can use it by paying a fee, and the application is hosted by the service provider. One can call it a new way of software distribution model (Mell et al., 2011). The fee paid to use the software is quite different than the conventional methods. Rather than paying a developed software upfront, users now pay a subscription, and sometimes add-on fees, to access it generally via internet browsers. This model enables the software industry and startups to reach more buyers by providing control over cash flow, remote support and automated and remote feature installation.

Besides the shift in software distribution, the Software as a Service (SaaS) model also shifts how software companies approach their business models; in fact, software companies are paying more and more attention to attracting new customers via investing in design and marketing teams. After these phenomenal changes in the industry and software owners, academic studies increased the speed of marketing software to users (Bantz et al., 2002).

Service design in SaaS has evolved significantly from the traditional software model. Research indicates that SaaS providers need to take a user-centric approach toward service design, emphasizing usability, continuous improvement, and regular interaction with the user base for feedback and development (Karaseva et al., 2015). This new model of offering software as a service resulted in users expecting high reliability, performance, and continuous availability of services, making these critical aspects of service design. Although the field of service design in SaaS has made substantial progress, many startups, particularly those in the technology sector, are still grappling with some significant challenges (Salamzadeh et al., 2015).

Startups, as important economic drivers, play a crucial role in generating new employment opportunities and fostering innovation but still encounter significant challenges. Establishing a new technology venture requires significant initial investments in money, time, and energy (Yankov, 2013). Regrettably, 95% of new product ideas fail (Hyder, S. 2019) due to issues such as cash flow (Berry, 2007) and poor product fit (Crowne, 2022).

These challenges are particularly pronounced in the startup scene. 90% of startups fail (Kotashev, 2022). This failure rate is 75% for venture capital-funded startups within the same time frame. Given the growing significance of the software as a service (SaaS) market, which is projected to reach USD 716.52 billion by 2028, understanding the key success factors for software startups is of paramount importance.

Moreover, in the face of these challenges and the competitive dynamics of the SaaS industry, a small number of influential companies have become the dominant forces. This makes it difficult for startups and smaller companies to carve out a position in the market. Requiring a significant amount of capital to maintain their operations, develop their products, and successfully compete with the big, well-funded companies in the market is one of their challenges (Cook et al., 2013; Salamzadeh et al., 2015; Giardino et al., 2015; Haase et al., 2019; Melegati et al., 2020).

In the face of these challenges, SaaS companies have also had to reconsider their customer acquisition strategies. User acquisition refers to the act that businesses do to get new customers (Zhang, 2021). In order to attract new customers and meet these evolving expectations, SaaS companies now approach their business model from a different perspective (Jayathilaka et al., 2021). These novel strategies include offering a freemium model, where basic services are provided for free with additional features available in paid plans (Naseer et al., 2016), and offering free trials, allowing potential customers to try the service before making any purchase (Leung et al., 2019). The aim is to acquire potential users with accessible entry points and prove the value of their services.

The freemium model, one of the most popular strategies, is to offer a bundle of basic features for free and offer advanced features for a fee as a premium package (Naseer et al., 2016). As a result, user acquisition cost is reduced since the users have wide access to test the tool for free. This reduces the entrance barrier for most of the software clients and affects the purchasing decision. Academic research that searches for ways of increasing the transition of free users to paid users suggests offering promotions to free users to become paid users (Jayathilaka et al., 2021).

Another popular strategy is the offering of free trials. Research has shown that free trials can significantly increase the conversion rate of users into paying customers (Leung et al., 2019). During a free trial period, users can use the software with full features for a limited period. This gives users a chance to explore and understand the value proposition of the software, increasing the likelihood of them becoming paying customers.

However, these pricing strategies are not helping early-stage startups to shine in the presence of industry-leading companies. Although there are multiple factors affecting the success of startups in terms of pricing structures, startups have to offer more disruptive offers to clients. The presentation software market deserves attention in this manner since there are many market leaders that outshine early-stage startups. Populated by an array of businesses, it is a specific niche dominated by a few key players, offering a diverse range of software products to create engaging and effective presentations (G2, 2023). Although presentation software are in our lives for a long time, there is a scarcity of research in the industry.

Faced with this complex reality, early-stage businesses are compelled to consider alternative strategies to traditional business models. In spite of the growing literature surrounding Software as a Service (SaaS) and its customer acquisition strategies, such as freemium models and free trial versions (Choudhary, 2007; Cusumano, 2010; Pujol, 2010; Ojala et al., 2011; Mehra et al., 2017; Liu et al., 2019; Shu et al., 2023), academic research is yet to extensively explore the domain of "lifetime deals". These lifetime deals, offering consumers perpetual access to SaaS products in exchange for a one-time payment, represent a unique selling proposition, particularly for new SaaS startups.

This new model of “lifetime deals” introduces a different set of considerations for the consumers, such as the perceived long-term value of the product, the financial viability of the company offering the deal, and the expected lifespan of the product. The factors influencing consumer preferences and purchase intentions may significantly vary from those typically observed in subscription-based SaaS products (Morrison, 1979; Sánchez-Fernández et al., 2007).

Furthermore, lifetime deals come with their own set of risks and benefits that can differently impact consumer behavior. On the one hand, unlimited usage without additional charges is an excellent benefit, particularly for heavy users of the product. Conversely, inherent risks, such as the potential for a company stops to operate, or the product becoming obsolete, could deter consumers, particularly those who are risk-averse (Weber et al. 1997).

Recognizing these unique dynamics and challenges, our research primarily aims to understand the customers’ preferences and purchase intention criteria within the context of SaaS “lifetime deals”. To this end, our research will investigate the critical service features in SaaS lifetime deals (such as price, human support, refund option, and regular feature updates) that affect consumer utility. We also aim to identify which consumer-related variables (perceived risk, perceived trust, perceived digital competency, usage frequency, usage period) impact consumer purchase intentions towards SaaS lifetime deals and whether the utility of service features could potentially moderate this relationship.

The main motivation behind this study is to comprehend the customer's perspective (their preferences, perceptions, and purchase intention). By doing so, the study will shed light on the benefits and risks associated with lifetime deals for consumers, and it will provide practical implications for service providers in this rapidly evolving market. In response to the growing interest in 'lifetime deals', as demonstrated by Google Trends data (Figure 1), our study also acknowledges the substantial gap in the academic literature on this topic. Despite the increasing prevalence of this strategy, academic inquiry into the factors influencing consumers' decision-making regarding lifetime deals is surprisingly scarce. This gap is even more pronounced considering the rise of such deals, as evidenced by Google Trends data (Figure 1), and the existing body of work's heavy focus on the provider's perspective. Figure 1 illustrates the interest in "lifetime deal" searches over time. The data is normalized so that the point of highest search interest during this period is set as 100, serving as a reference point for all other values. For instance, if the value for a certain point in time is 50, it indicates that the search interest for a "lifetime deal" at that time was approximately half of its peak popularity during the specified period. Conversely, a value of 100 signifies that the search interest reached its maximum compared to other moments within the given timeframe. A score of 0 indicates that the data available was too limited to reliably calculate the search interest, and the absence of a value at a certain denotes insufficient data for that specific time period (Google. (n.d.).

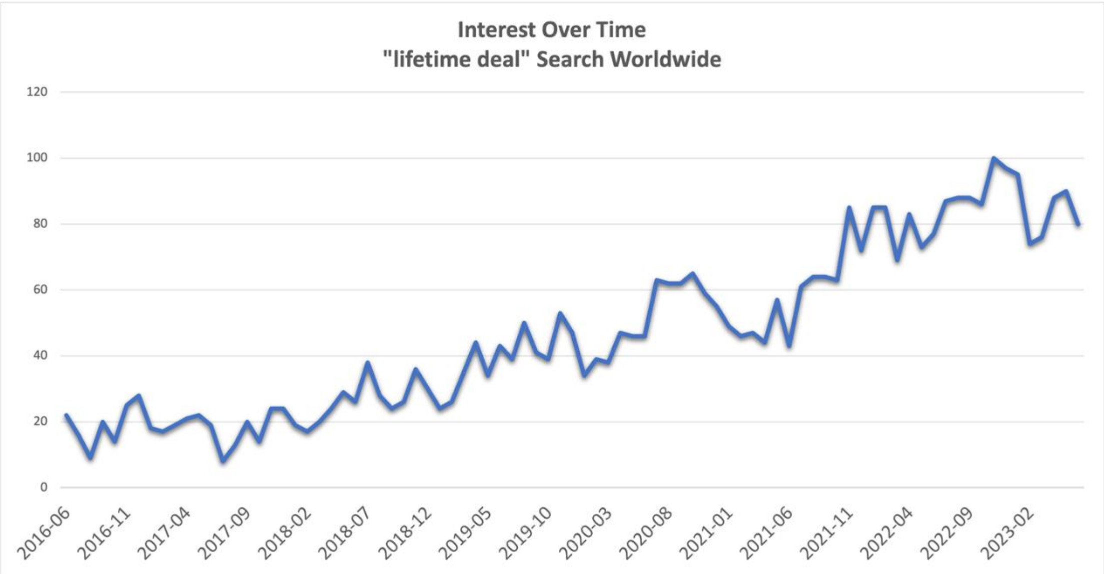

Figure 1. Search volume of “lifetime deal” (Source: Google Trends, 2023)

Recognizing this research gap, this thesis embarks on a comprehensive examination of the factors affecting the lifetime SaaS purchase preferences and intentions of consumers, with a particular focus on the presentation tool category. Hence, by examining these factors, our research fills an important gap in the field of SaaS, while providing insights that could reshape our understanding of alternative SaaS business models. The central research questions are as follows:

In the design of SaaS lifetime deals, what are the critical service attributes for consumers?

How do these critical service attributes in the design of SaaS lifetime deals and other relevant consumer-related variables, such as perceived risk and digital competency, affect consumer purchasing intentions?

To tackle these research questions, after a comprehensive literature review, firstly, we identified the important attributes for lifetime deals: price, human support, feature updates, and refund option. After that, we conducted a focus group study to glean expert opinions on the desired attributes, and we determined the levels of the attributes. Next, we designed a choice based conjoint analysis (Desarbo et al., 1995) using experimental design. After determining 4 attributes, we identified total 9 levels of the attributes. We extensively examined the attribute-level interactions in our conjoint analysis using a full factorial design. This design, which is frequently employed in experimental designs, combines every set of the detected attribute levels, leading to a total of 24 distinct profiles (Montgomery, 2017). This method ensures a thorough understanding of the individual and combined effects of each attribute on customer decisions (Desarbo et al., 1995). In order to get respondents to compare all profiles we needed to show 276 comparisons (every combination of the different 24 distinct profiles), that’s why we reduced the number of product profiles that is large enough to determine the relative weight of each attribute while still being small enough to be included in a survey. As a result, in the survey, each respondent was shown 2 different products at a time and asked to pick one. All respondents did this 10 times. In this way, every respondent saw 10 comparisons instead of 276 comparisons. To make this valid, every respondent saw 10 different comparisons. We collected responses from 2195 distinct respondents. Instead of using the “rating-based conjoint” method (Green et al., 1990), where people are asked to give ratings to products from 1 star to 10 stars, we used “choice-based conjoint” (Louviere et al., 1983). Because rating profiles is a more difficult task for the respondent, and it may cause inconsistent choices. Yet, choosing products is a natural task that consumers do every day (Chapman et al., 2019), and it leads to greater external validity (Elrod et al., 1992). That's why we chose choice-based conjoint analysis.

By using the mixed logit model (Hensher et al., 2003), we identified consumer utilities with respect to each attribute. After that, to find individual-level coefficients, we used the hierarchical Bayesian model (Gelman et al., 2003).

We purposefully separated utility and purchase intention investigations. While the utility is an emotional and subjective assessment of the consumer based on the relevant attribute (Bagozzi et al., 1999), the purchase intention represents the likelihood of a customer deciding to buy a product. It is frequently influenced by pragmatic considerations like financial capability and other material considerations (Cheng, Fu et al., 2011). It means a positive effect on utility does not automatically translate to an increase purchase intention. Hence, we separated utility and purchase intention to elucidate the effect of the attributes on the utility, to observe the effect of consumer-related variables such as perceived risk, perceived trust, perceived digital competency, usage frequency, and usage period on the purchase intention, and to discover the moderations of the key SaaS lifetime attributes' utilities in the effects of consumer-related variables on purchase intention.

Our study explores various factors influencing the perceived utility of SaaS lifetime deals and their subsequent purchase intentions. As per our initial hypotheses and corresponding results, we discovered that refund options, feature updates, and human support positively impact a product's perceived utility. Conversely, price displays a negative correlation with utility, aligning with our preliminary assumptions.

Upon closer inspection of our regression analysis, we found intriguing insights. In line with our initial hypotheses, and as evidenced by the results, the usage period, perceived trust, usage frequency, and perceived digital competency, all have positive effects on purchase intention. Furthermore, frequent users of the presentation tool demonstrate a greater willingness to pay for the feature update option. In addition to it, as customer trust a company, the necessity for refund options becomes less impactful on their purchase decisions. Also, the utility of price is found to moderate the perceived risk, reducing its negative impact on purchase intention. Interestingly, while the utility of a refund moderates perceived trust, the effect is negative. Similarly, the utility of feature updates has a moderation effect on usage frequency, which is quite strong and significant.

Our research sheds new light on the nuances and complexities of customer decision-making in the context of purchasing SaaS lifetime deals. One key aspect of our study was to distinguish between the utility derived from SaaS lifetime deals and the purchase intention. While the key attributes of SaaS lifetime deals certainly influence their perceived utility, our findings reveal that this utility doesn't not consistently predict or moderate purchase intention. Though some hypotheses were validated and others were not, these findings underscore the need for further investigation in this novel and under-studied area.

This research dives deep into how customers make decisions in a novel area: lifetime deals in Software as a Service (SaaS). We're exploring what makes customers tick and why they decide to buy these deals, which hasn't been studied much before, making this work quite novel.

This research makes significant theoretical and practical contributions to the field of Software as a Service (SaaS) and consumer behavior. On a theoretical level, this study delves into the relatively unexplored territory of lifetime deals within the SaaS business model. It enhances our understanding of how customers perceive utility from various service attributes like price, human support, refund options, and regular feature updates. It also identifies how customer-related variables - including perceived risk, trust, digital competency, usage frequency, and usage period - directly influence purchase intention. Furthermore, it explores the moderating effects of the utilities of these service attributes on the relationship between customer-related variables and purchase intention, thereby broadening our understanding and supplementing existing theories of consumer decision-making in the context of SaaS lifetime deals.

From a practical standpoint, this research provides actionable insights for early-stage SaaS businesses seeking to optimize their lifetime deal offerings. It offers evidence-based guidance on how to adjust service features to maximize perceived utility, thereby moderating the impact of consumer characteristics on purchase intention. By better understanding how different aspects of their offerings can influence the interplay between consumer characteristics and purchase decisions, SaaS businesses can strategically design their lifetime deals to enhance customer acquisition and satisfaction. Furthermore, these findings can aid SaaS businesses in structuring their offerings in a way that balances immediate revenue generation with long-term customer retention and loyalty. Lastly, this research lays the groundwork for future studies aiming to further explore these dynamics and test the generalizability of these findings in other software markets. This thesis is organized as follows: The literature review section provides the theoretical groundwork, while the hypothesis development section proposes our hypotheses based on identified literature gaps. The research design section outlines our data collection and evaluation methods, including a focus group, choice-based conjoint analysis, Mixed Logit Modeling, Hierarchical Bayesian Modeling, and factor score regression. Our findings are presented and analyzed in the subsequent section, and the conclusion section contextualizes these results within the broader academic and SaaS industry. Our aim throughout is to shed light on consumer behavior in SaaS lifetime deals, providing valuable insights for both scholars and industry practitioners.

CHAPTER 2: LITERATURE REVIEW

This section will review the literature related to service, its characteristics, and the distinctions between physical goods, in-person services, and online services. The theoretical foundations for service design will be identified by reviewing existing studies in the field. We will then delve into the relatively understudied area of "lifetime deals" in the context of the Software as a Service (SaaS) model, an emerging strategy providing consumers with perpetual access to a service for a one-time payment. This review will attempt to outline the foundational concepts related to lifetime deals, their benefits, and the challenges they present. The focus will then shift to exploring the relationships between the service attributes (pricing, human support, future updates, and refund options) and the customer characteristics (perceived trust, perceived risk, perceived digital competency, usage period, and usage frequency) within the SaaS model. Furthermore, the section will cover the challenges faced by startups, especially financial limitations and achieving product-market fit. Notably, this literature analysis primarily aims to show a large gap on the topic of lifetime deals especially in SaaS products, which, in our belief, will highlight the need for this study.

2.1. Service

Service is defined as an action performed by an entity on behalf of another, an asset with inherent value that is transferred from the provider to the recipient and can be contained within other services (referred to as sub-services). Electronic services (or e-services) are characterized by their ability to be automatically summoned anywhere, anytime, with minimal constraints on the time and location of request, although there may be a delay between the request and execution due to resource constraints or human intervention required in the performance of the service (O'Sullivan et al., year). "Services are a form of product that consists of activities, benefits, or satisfactions offered for sale, that are essentially intangible and do not result in the ownership of anything." (Kotler et al., 2012, p. 224).

The contrast between online and physical services may be more fully examined by extending the idea of services. Online services can offer distinctive qualities that are not shared by physical services because of their nature. Digital technology, for instance, makes it possible for online services to be immediate and customized (Rust et al., 2003).

Online services may be used at any time and from any location, considerably increasing their usefulness. actual services, however, are often restricted by their actual location and open hours.

Consumers' purchase intentions might also vary across physical and online businesses. People are more inclined to trust and buy physical services because they are more tangible, but online services have a harder time earning confidence because of their lack of trust (Kim et al., 2008). Services are dangerous by nature due to their intangibility (Zeithaml et al., 1985), but this risk is increased in the online context.

The decision-making process for purchasing physical goods, physical services, and online services share some similarities, but they also bear significant differences due to the unique characteristics of each category (Rathmell, 1966; Butler et al., 1998; Lovelock et al., 2004; Pires et al., 2004).

Physical goods are tangible, and consumers can evaluate them prior to purchase. The traditional consumer decision-making model for physical goods includes stages like need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase evaluation. Consumers can base their evaluation on product attributes such as price, quality, and brand reputation (Martín-Ruiz et al., 2008).

For physical services, the decision-making process is more complex due to their intangible nature. Consumers rely more heavily on personal sources of information, such as word of mouth, and on the reputation of the service provider (Arslanagić et al., 2013). The evaluation of service quality also includes additional dimensions like responsiveness, assurance, and empathy of the service personnel, in addition to tangibles and reliability (Idayati et al., 2020).

As for online services, the decision-making process becomes even more complex due to the heightened intangibility and potential risks. Trust plays a vital role in this process (Kim et al., 2008). Consumers rely on various cues to establish trust, such as the design and usability of the website, third-party seals of approval, user reviews, and the provider's transparency about their policies (McKnight et al., 2002). Online service providers can enhance trust and reduce perceived risk through strategies like providing comprehensive and accurate service information, ensuring a secure transaction environment, and offering excellent customer service (Liu et al., 2005).

Scholars (Lovelock et al., 2004) suggested four primary characteristics in terms of service characteristics for both physical and online services: intangibility, heterogeneity, inseparability, and perishability (IHIP).

Intangibility refers to the fact that services, unlike goods, do not have a physical presence and cannot be touched or seen before they are purchased (Zeithaml et al., 1985). This characteristic is heightened in the online environment because there are no physical clues or personnel for customers to interact with. The challenge for online service providers, therefore, is to provide sufficient information and reassurance to customers about the quality and value of the service. Intangibility is magnified in the online environment due to the lack of physical presence, making it harder for consumers to evaluate prior to purchase (Kim, et al. 2008).

Heterogeneity refers to the variability in the quality of service delivery, as services are typically delivered by people and can vary depending on who provides them and when and where they are provided (Zeithaml et al., 1985). Online services have an advantage in managing heterogeneity better through automation and standardization of service processes, leading to more consistent service quality (Rust et al., 2003).

Inseparability, the characteristic that services are produced and consumed simultaneously, is also enhanced in the online context. In physical service provision, customers interact with service personnel, which is an integral part of service delivery. However, in the online environment, these interactions are replaced by interfaces, and the simultaneous creation and consumption of services often occur without any face-to-face interaction, making the customer experience even more critical (Méndez-Aparicio et al., 2020)

Perishability, the concept that services cannot be stored for future sale or use, remains a significant challenge in the online environment. The real-time nature of online service delivery means that service providers must manage demand and capacity effectively. If demand exceeds capacity, customers may experience delays or receive a lower-quality service. Conversely, if capacity exceeds demand, the service provider incurs costs without generating revenue (Lovelock et al., 2004).

By more effectively organizing and arranging the people, infrastructure, communication, and material components of a service, service design aims to enhance the interaction between the service provider and customers. It is beneficial to plan, manage, and optimize an organization's operations from a single point of view in order to deliver services that are user-friendly, competitive, and pertinent (Moritz, 2005).

User experience design, information and management sciences, ethnography, and other fields are all included in the area of service design, which is both a practice and a subject of study. Its primary goals are to enhance the interfaces between service systems and the people who use them (Stickdorn et al., 2010). It is inherently multidisciplinary and integrative.

According to Polaine et al. (2013), the definition of service design is a transition from the process of creating objects (products) to the process of organizing and planning the people, infrastructure, communication, and material components of services. They claim that the purpose of service design is to enhance both user and staff experiences via the planning, coordinating, and optimization of an organization's internal processes and external customer encounters.

Further emphasizing that service design entails more than just creating systems. Meroni et al. (2011) argue that it also entails a change of perspective from the system level to the strategic level. It entails comprehending and integrating solutions into current service systems and cultural norms, developing new cultural norms, and sometimes even restructuring the company.

2.2. Software as a Service (SaaS)

SaaS, or Software as a Service, represents a distinct departure from conventional software methodologies. This model usually facilitates a subscription-based approach whereby users incur a continuous monthly service charge rather than procuring software licenses (Satyanarayana, 2012).

Service and Software as a Service (SaaS) share a common core as both are intangible offerings that provide value to the customer. However, they differ significantly in their delivery, operational model, and specific characteristics.

Services, in their traditional sense, refer to activities, benefits, or satisfaction offered by one party to another. They are typically characterized by intangibility, inseparability, heterogeneity, and perishability (Kotler et al., 2012). Services are diverse and may include various sectors such as hospitality, healthcare, professional consulting, and more. The provision of services often requires a substantial amount of human labor and often entails direct interactions between service providers and consumers (Johns, 1999).

Yet, SaaS is a subset of services that expressly relates to a software delivery mechanism. In the software as a service (SaaS) business model, a third-party supplier hosts software and makes it accessible to users online, generally via a subscription model (Godse et al., 2009). The intangibility of SaaS is comparable to that of traditional services but is increased because the offering is entirely online (Eggert, 2006). SaaS also tends to be less heterogeneous than traditional services due to its high level of standardization and automation (Schneider et al., 2004). The inseparability characteristic of traditional services is less obvious in SaaS, as the production and consumption of the service do not require real-time interaction between the provider and consumer (Parasuraman et al., 1985).

The fundamental principles underpinning SaaS are relatively straightforward. The SaaS provider is responsible for maintaining, securing, and keeping every work unit live in contrast to the traditional software model where companies host the server on-premise and do all technical work by themselves (Greschler et al., 2002). The SaaS application is accessed via the Web by using a standard web browser as opposed to the traditional software where an installed application is necessary to use the software. Since the SaaS provider has to provide the service and all work units on their own data center, they have to provide Vendor Support for any issues or requests. In general, the SaaS provider provides new features multiple times per year (Ju et al., 2010).

The SaaS model has become increasingly relevant in the startup ecosystem, especially due to its scalability, ease of deployment, and cost efficiency (Benlian et al., 2009). Startups can utilize SaaS to provide innovative solutions to their customers with lower up-front costs (Choudhary, 2007).

Since the popularity of SaaS, several vendors have provided SaaS-based products, and it makes selecting a proper SaaS product a key issue for purchasers who need to analyze multiple selection parameters and decide based on the analysis (Gartner, 2019). For different types of SaaS and different purchaser profiles (individual and organizational), the purchase considerations change. In general, for organizations, reliability, scalability, and uptime are the key factors (Bhardwaj et al., 2010), specifically for sales force automation (SFA).

One important aspect impacting the adoption and use of Software as a Service (SaaS) offered by new businesses is perceived trust in it. Startups sometimes struggle to establish themselves as reliable companies in the eyes of potential consumers, particularly those in the SaaS industry. This trust, which is viewed as a startup's reliability, is the conviction that the business will consistently provide the promised services without interruption or failure. In SaaS, dependability also refers to reliable service delivery, data confidentiality, and quick problem resolution—all of which are essential for fostering user confidence (Heart, 2010).

Additionally, perceptions of new businesses' dependability, honesty, and general trustworthiness are crucial. The dependability of the service and the provider's credibility are crucial since SaaS is a model where the provider hosts and maintains the software application. On the other side, honesty refers to the startup's openness and integrity in its interactions with consumers. According to Gefen et al. (2003), this calls for transparent communication, genuine marketing, and keeping the company's pledges. For new SaaS firms, building perceived trust through dependability, reliability, honesty, and trustworthiness is crucial since it affects potential customers' adoption decisions, continued loyalty, and the company's long-term performance (Bharadwaj et al., 2012).

Consumers' buying decisions may be significantly influenced by perceived risk in the Software as a Service (SaaS) environment, particularly when it comes to new startups. Consumers may worry about possible fraud when considering making a purchase from a young firm. This can involve exaggerating the capabilities of the program or making even graver accusations like financial fraud. Customers' desire to engage in a purchase transaction is directly influenced by their perception of the risk of fraud (Kamalul Ariffin et al., 2018).

Perceived risk is also influenced by worries about program performance and opportunistic behavior. Due to the intangible nature of SaaS services, consumers frequently worry about whether the startup's software will deliver on its promises (Hong, 2015). The perceived risk can be further increased by worries about opportunistic actions, such as the corporation changing conditions after a purchase, introducing hidden costs, or taking advantage of customers in various ways (Pavlou et al., 2004).

Trust in the SaaS vendor community, perceived capabilities, and perceived reputation of SaaS vendors are the main factors when deciding to purchase SaaS or not. That is why there is a positive effect of perceived trust and a negative effect of perceived risk on SaaS purchase intention (Heart, 2010), and when perceived risk is decreased, the intention to adopt a SaaS product increases (Wu et al., 2011, Kuciapski et al., 2021).

The adoption of Software as a Service (SaaS) products is significantly influenced by perceived digital competency or confidence in one's capacity to use digital tools and applications. SaaS solutions are frequently used online. Therefore users must be familiar with utilizing digital devices and have a certain level of digital literacy (Vieru et al., 2015). Users who view themselves as having a high level of digital competency may be more ready to experiment with and accept new SaaS solutions because they feel confident navigating novel digital environments and can handle any possible technological challenges.

Additionally, customers who are confident in their capacity to fix problems with digital devices may be more likely to try SaaS solutions supplied by startups, which may have more problems than more established companies. This is because these people think they possess the knowledge necessary to solve any possible issues. Similar to this, a user's degree of comfort using digital devices at home might influence how they use SaaS, particularly in light of the expanding popularity of remote work and growing reliance on cloud-based software solutions. The adoption and effective usage of SaaS solutions might be facilitated under these circumstances by the perceived digital competence (Vieru et al., 2015).

Both in physical marketplaces and in digital ones like the Software as a Service (SaaS) sector, price significantly influences consumers' purchasing inclinations. Price and purchase intention has a negative connection, according to traditional economic theory and empirical research: when the price rises, buy intention drops, and vice versa (Muljani et al., 2019) Customers frequently aim to enhance their utility or happiness while decreasing expenditures, which is why this is the case. Potential clients' purchasing intentions may decrease if they feel that a product or service's pricing is excessively high.

However, the effect of price on consumers' decision to buy is frequently complex and can be influenced by a number of different variables, including perceived value, quality, and affordability. For instance, studies have shown that customers may be prepared to pay more even when similar goods or services are offered at a lower cost if they believe a high price to be a sign of greater quality (Dodds et al., 1991). This phenomenon is especially important in the SaaS sector, as vendors frequently distinguish their products based on features and degrees of quality. Similar to how perceived value affects perceived advantages against perceived costs, perceived value affects purchasing intentions. Customers are more likely to buy anything if they believe that the advantages exceed the disadvantages (Zeithaml, 1988).

In the Software as a Service (SaaS) industry, human support is essential for boosting the user experience and promoting customer retention. Users may occasionally experience technical issues or need assistance in understanding certain functionality because SaaS apps are frequently complicated and distributed via the internet. In these situations, customer happiness and returning customers are substantially impacted by the availability and quality of human service (Schueller et al., 2017). Additionally, human support may add a personal touch that raises customer perceptions of the quality of the service, giving SaaS businesses an advantage in a crowded market.

SaaS companies provide a variety of human support services, from conventional phone and email help to more contemporary options like live chat and social media support. According to research, prompt and efficient customer service may lower churn rates and raise customer lifetime value, two key performance indicators for the subscription-based SaaS business model (Jamal et al., 2006).

The Software as a Service (SaaS) business model emphasizes future updates, which allow continuous software advancement and refinement to match evolving customer needs and technological advancements. SaaS updates are often frictionless, requiring no action from the user and causing no downtime, in contrast to conventional software, where upgrades frequently entail substantial work and expense from the user's side (Choudhary, 2007). As customers may always access the most recent and optimum version of the program without the inconveniences often associated with software upgrades, this can increase customers' perceived utility of the software (Fleischmann et al., 2016).

Future updates' frequency and quality serve as a value proposition for SaaS products. Customers who subscribe to a SaaS product are not only purchasing access to the software as it exists now; they are also making an investment in its further improvement. SaaS providers may increase their perceived value and competitive posture by offering frequent, significant updates that show their dedication to innovation and ongoing development (Benlian et al., 2009).

Refund policies are a crucial part of Software as a Service (SaaS) products, both as a layer of protection for clients and a way for companies to demonstrate their faith in the quality of their work. The assurance of a refund, especially from new or lesser-known vendors, might reduce potential consumers' worries over the financial risk involved in acquiring a subscription. In addition to increasing conversion rates, a robust return policy can stimulate experimentation and build consumer confidence (Di Fatta et al., 2018).

Because the SaaS market frequently involves long-term commitments and intangible products, refunds can be particularly important. Customers are unable to completely analyze the product prior to purchase, unlike tangible goods. Therefore, the option to get a refund if the service does not meet their expectations or needs can play a critical role in their purchase decision. By reducing the perceived risk related to the purchase of SaaS subscriptions, giving refunds might be viewed as a type of "risk reversal" (Petersen et al., 2010).

2.3. Startup Challenges

Startups, as important economic drivers, play a crucial role in generating new employment opportunities and fostering innovation. However, establishing a new technology venture requires significant initial investments in money, time, and energy (Yankov, 2013). Regrettably, 95% of new product ideas fail (Hyder, S., 2019) due to issues such as cash flow (Berry, 2007) and poor product fit (Crowne, 2022).

Despite the opportunities presented, startup survival rates are daunting. 90% of the startups fail (Kotashev, 2022). This failure rate is 75% for venture capital-funded startups within the same time frame. Given the growing significance of the software as a service (SaaS) market, which is projected to reach USD 716.52 billion by 2028, understanding the key success factors for software startups is of paramount importance (Fortune Business Insights, 2022).

MacMillan et al. (1987) propose four holistic dimensions method that categorizes the challenges that startups have often. The four dimensions, namely team, product, financial, and market, will provide a balanced perspective for exploring the pathways to success for software startups.

There are 10 common challenges of early-stage startups categorized by the four holistic dimensions (Giardino et al., 2015).

Table 1. Startup's common challenges

Challenge No.	**Challenge**	**Description**	**Dimension**
1	Thriving in technology uncertainty	Developing technologically innovative products, which require cutting-edge development tools and techniques	Product
2	Acquiring first paying customers	Persuading a customer to purchase the product, e.g. converting traffic into paying accounts	Market
3	Acquiring initial funding	Acquiring the needed financial resources, e.g. from angel investors or entrepreneurs' family and friends	Financial

Table 1 (Continued). Startup's common challenges

4	Building entrepreneurial teams	Building and motivating a team with entrepreneurial characteristics, such as the ability to evaluate and react to unforeseen events	Team
5	Delivering Customer Value	Defining an appropriate business strategy to deliver value	Market
6	Managing Multiple Tasks	Doing too much work in a relatively short time, e.g. duties from business to technical concerns	Team
7	Defining Minimum Viable Product	Capturing and evaluating the riskiest assumptions that might fail the business concept	Product
8	Targeting a Niche Market	Focusing on specific needs of users willing to take risks on a new product, such as early-adopters and innovators	Market
9	Staying Focused and Disciplined	Not being particularly sensitive to influences from different stakeholders, such as customers, partners, investors and competitors (both actual and potential)	Team
10	Reaching the Break-even Point	Balancing losses with enough profits to continue working on the project	Financial

In the context of monopolistic markets, large firms often overlook certain challenges outlined in this chart, such as financial and team dimension issues, which competitors aiming to capture a market share face. However, these challenges, particularly financial ones, pose significant problems for early-stage startups.

2.4. SaaS Deals

SaaS providers use some strategies to acquire users at a lower cost. Providing a freemium product or a free trial version are popular strategies (Li, 2022). Offering a freemium product means there are at least two plans, and the first plan is free. The main idea is to acquire users at the lowest price (free) and upgrade them in the future to one of the paid plans (Pujol, 2010). A free trial is a strategy where potential customers can use a product or service for a limited time without any charge. The primary objective is to allow users to experience firsthand the benefits and functionalities of the product or service, thereby reducing their perceived risk and uncertainty and encouraging them to become paid customers after the trial period ends (Mehra et al., 2017).

Both strategies decrease the uncertainty of the SaaS product and lead to increased lead to paid conversion rates (Liu et al., 2019; Shu et al., 2023). In the existing literature, so many different aspects of these business models have been discussed, such as the optimal trial length of the free trial duration (Cheng et al., 2014; Zhang et al., 2022; Hua et al., 2019; Shu et al., 2023), the feature coverage of the free trial and the freemium version and cannibalism (Faugère et al., 2006; Cheng et al., 2014), network effects (Cheng et al., 2010; Parker et al., 2000; Parker et al., 2005), and piracy.

In spite of the growing literature surrounding Software as a Service (SaaS) and its customer acquisition strategies, such as freemium models and free trial versions (Pujol, 2010; Mehra et al., 2017; Liu et al., 2019; Shu et al., 2023), academic research is yet to extensively explore the domain of "lifetime deals". These lifetime deals, offering consumers perpetual access to SaaS products in exchange for a one-time payment, represent a unique selling proposition, particularly for new SaaS startups.

Although directly related studies are scarce, the concept of lifetime deals intersects with numerous strands of academic inquiry, such as consumer behavior, perceived value, perceived risk, and pricing strategies (Monroe, 2003; Demirgüneş et al., 2015). For instance, lifetime deals, while eliminating ongoing subscription fees, can present a greater perceived risk due to the significant upfront cost and uncertainty concerning the service's future viability (Mitchell, 1999). Hence, a deep understanding of how these and other factors influence consumers' decisions to purchase lifetime deals becomes crucial.

A novel trend in the SaaS industry is the offering of lifetime deals. These deals diverge from the traditional SaaS subscription model by requiring a one-time payment for perpetual service access. They offer a distinctive value proposition to customers. Notably, these deals engage customers in a long-term relationship with the provider, a factor known to increase customer loyalty and lifetime value (Gupta et al., 2004).

Despite the insights provided by established fields, direct research addressing this new trend of lifetime deals is scarce. This represents a notable gap in the literature, particularly considering the distinct characteristics and potential implications of lifetime deals within the SaaS sector.

For the purposes of this study, we will primarily focus on the challenges outlined above, specifically those related to financial and product-market fit. Offering lifetime deals can potentially increase revenue and address some cash flow issues. Importantly, they also provide an opportunity for startups to garner valuable feedback, which can help accelerate product development and achieve a better product-market fit more rapidly. Startups have a unique advantage over larger companies in their ability to 'pivot' or adapt their business models swiftly when current strategies prove unfruitful (Blank, 2007).

The aim of this study is to fill the literature gap by investigating the influence of the key SaaS lifetime attributes (price, feature update, refund option, human support) on the utility, examining how consumer-related variables (usage frequency, usage period, perceived risk, perceived trust, perceived digital competency) impact purchase intention, and the moderating effects of the utilities of these attributes on the relationship between customer-related variables and purchase intention, Hence, this research seeks to delve into the specific factors shaping consumers' preferences and purchasing intentions in the context of lifetime SaaS deals. By leveraging relevant theoretical perspectives and empirical findings, this study aims to contribute to the SaaS literature with a robust model to understand and predict consumer behavior related to lifetime deals. These insights could offer SaaS providers invaluable guidance to enhance their offerings and strategies in the competitive SaaS market landscape (Teece, 2010).

CHAPTER 3: HYPOTHESES DEVELOPMENT

In this section, we propose key attributes and factors that influence customers' utility and purchase intentions in the context of Software as a Service (SaaS) lifetime deals. We propose two research models: Model 1 shows the effects of the key SaaS lifetime deal attributes on the utility. Model 2 showcases the direct and moderator effects of the attributes and consumer-related variables on purchase intention. Our hypotheses contain four main attributes: price, refund option, feature updates, and human support. Each attribute is examined for its effect on a customer's utility, essentially the power of the attribute, and then its moderator effect on the purchase intention. In parallel, we focus on five customer-related variables: perceived risk, perceived trust, perceived digital competency, usage frequency, and usage period. We investigate the direct effects of the consumer-related variables on the purchase intention and examine the relationship between consumer-related variables and the key SaaS lifetime attributes on the purchase intention.

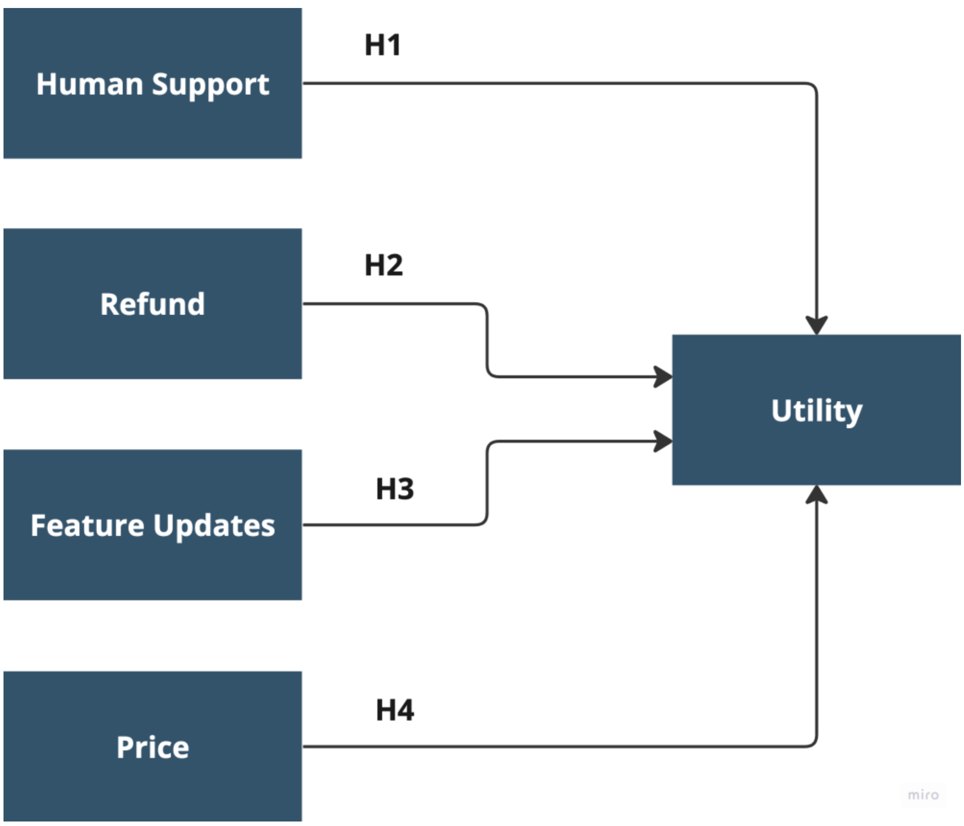

Figure 2. Research Model on the Effects of the Key SaaS Lifetime Attributes on Customer Utility

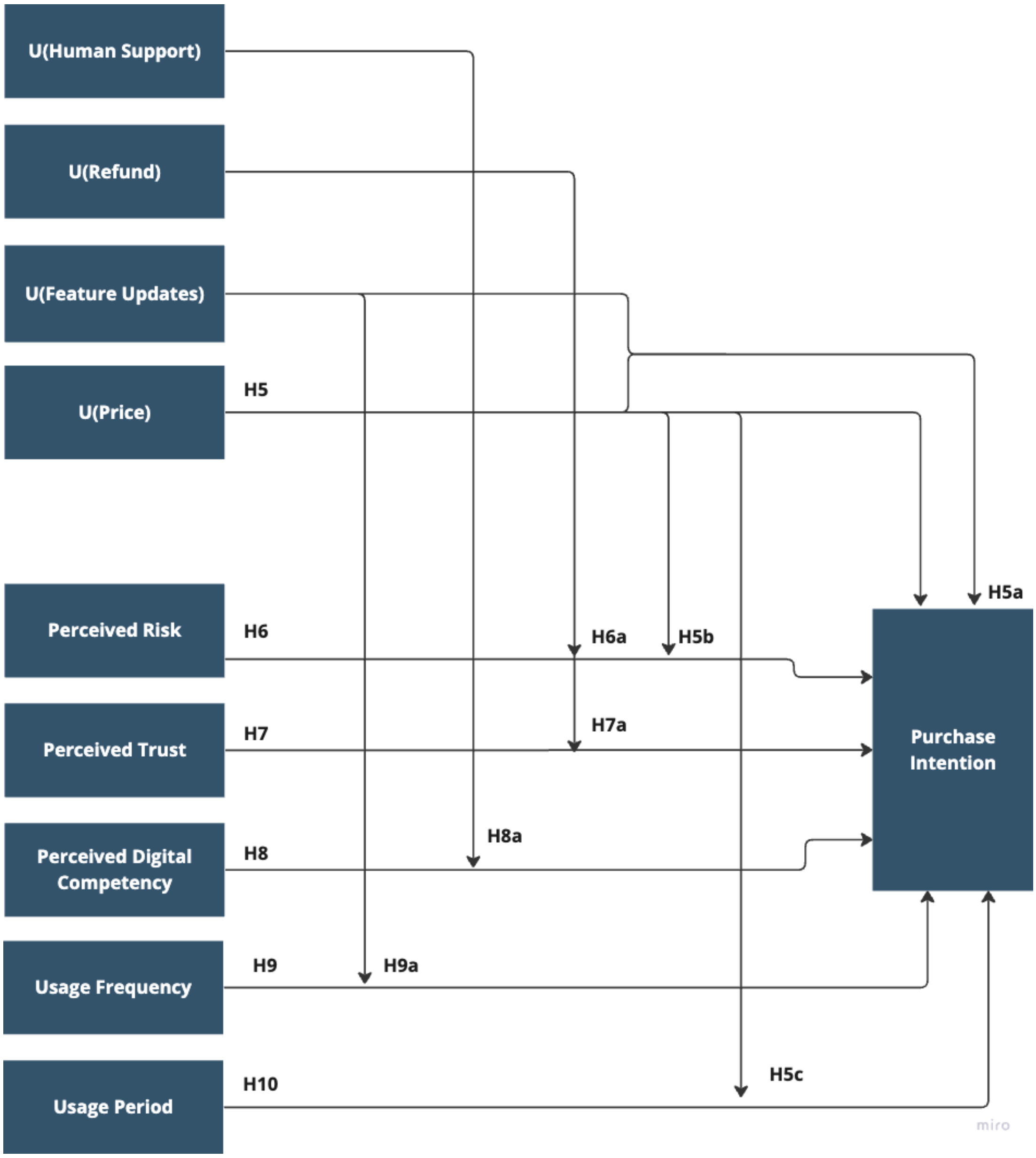

Figure 3. Research Model on Factors Affecting SaaS Lifetime Purchase Intentions

The fundamental difference between utility and purchasing intention serves as the foundation for these ideas. Although utility and purchase intention seem similar at first glance, they are fundamentally different concepts, each driven by distinct factors. Utility indicates an overall evaluation based on the relevant attribute and tends to be more aligned with emotional and subjective assessment (Bagozzi et al., 1999). In contrast, purchase intention represents the likelihood of a customer deciding to buy a product and is frequently influenced by pragmatic considerations (Spears et al., 2004).

It is crucial to analyze these separately because a positive effect on utility doesn't automatically translate to an increase in purchase intention. As Ajzen (1991) explains in the theory of planned behavior, the intention to perform a behavior is not solely driven by one's positive or negative evaluation of the behavior (which could be analogous to utility in this context) but also by other factors such as perceived behavioral control (similar to financial and material considerations). When investigating purchase intention, we treat utility as a dependent variable and hypothesize that some consumer-related variables such as perceived risk, perceived trust, perceived digital competency, usage frequency, and usage period may affect the purchase intention, and the utility of the attributes may moderate the effects of the consumer-related variables on the purchase intention. This comprehensive methodology offers a detailed understanding of the numerous variables influencing consumer choice for SaaS lifetime deals.

Customer support is recognized as a crucial determinant in purchasing decisions, particularly for software products, given its influence on customer satisfaction, trust, and perceived value. High-quality customer support can address potential issues, provide the necessary information, and enhance the user experience, thereby exerting a positive impact on purchasing decisions (Anderson et al., 1997).

Supporting this notion, Homburg et al. (1999) identify that responsive and competent customer support can enhance customer satisfaction, subsequently increasing the propensity for customers to engage in a purchase. Parasuraman et al. (1985) further highlight customer support as a critical component of overall service quality, with significant implications for customer perceptions of both the company and its product offerings.

Furthermore, customer support can contribute to the perceived value of software, as customers frequently consider the quality of such support when evaluating the overall worth of a product (Anderson et al., 1997). Timely and effective support can enhance customers' perceptions of the software's value, encouraging them to favor it over competing offerings.

Customer support is integral across a variety of products and services, but its role is especially critical for SaaS lifetime deals. Such deals ask customers to make a significant upfront payment for indefinite service access, necessitating a greater degree of trust and assurance from the service provider. Customers are essentially investing in the long-term reliability and viability of the service. Hence the presence of robust, responsive customer support becomes pivotal in their decision-making process (Doney et al., 1997; Morgan et al., 1994).

Lifetime deals inherently mean longer relationship duration with the SaaS provider. Over this extended period, the customer might encounter various issues or need assistance with updates or feature changes. The quality of customer support, therefore, is not just a matter of immediate concern but impacts the perceived value of the deal across its entire lifespan (Gwinner et al., 1998).

Moreover, many SaaS products can be technically intricate, requiring customers to often seek support for navigating the software's functionalities and maximizing their use. Effective and competent customer support can serve to mitigate perceived risk, enhance perceived value, and foster a sense of trust and confidence in the SaaS provider (Parasuraman et al., 1985).

Furthermore, startups or less established companies often offer SaaS lifetime deals. In such contexts, customer support assumes an even greater significance as it offers reassurance to customers about receiving adequate service and attention, even if the company is yet to establish a significant market presence or reputation (Pérez et al., 2013)

Building on the integral role of customer support in influencing the perceived utility of SaaS lifetime deals, it is prudent to consider the unique value proposition of human support. The intricate nature of SaaS products and the substantial commitment involved in lifetime deals often compel customers to seek reassurances, which human support, marked by its personal interaction and adaptability, is particularly well-equipped to provide (Keefer et al., 2014). Therefore, we propose the following hypothesis:

H1: Human support positively affects the perceived utility of SaaS lifetime deals.

The concept of a refund policy, particularly its offering, and duration, plays a pivotal role in influencing consumer purchase decisions, especially in software acquisition. Such a policy affects various factors that consumers typically consider, such as perceived risk, trust in the seller, and overall satisfaction (Chen et al., 2015; Wood, 2001). A robust and well-structured refund policy has been demonstrated to diminish perceived risk, a crucial determinant in consumer decision-making in online shopping environments (Chen et al., 2015). Complementing this, Wood (2001) found that the leniency of return policies significantly impacts consumer decisions in remote purchase scenarios, such as online software purchases.

Delving further into the effects of a favorable refund policy, Grewal et al. (1998) suggested that it positively influences customers' perceptions of acquisition value, transaction value, and behavioral intentions – all of which are vital facets of the purchase decision-making process. Therefore, the strategic design of refund policies is a critical consideration for companies aiming to maximize customer confidence and, by extension, sales.

Refund policies assume unique importance in the context of SaaS lifetime deals due to the high upfront cost and enduring commitment these deals entail. These factors can create substantial perceived risk for the customer due to uncertainty about the long-term viability and value of the software and concerns about the provider's ongoing support and commitment (Bartolini et al., 2016).

In this context, a robust refund policy serves as a risk mitigation mechanism, assuaging potential customer anxieties by providing an exit option should the product fail to meet expectations or requirements change (Moorthy et al., 1995). This assurance can substantially enhance customers' perceived utility of lifetime deals by offsetting the inherent risks associated with a long-term commitment.

Moreover, a favorable refund policy can strengthen trust in the provider, a key determinant of purchase intention in the context of SaaS lifetime deals. As shown in studies by (van der Werff et al., 2019), trust in a provider significantly influences purchase decisions, particularly in online environments where consumers have to rely on the company's goodwill to honor its commitments. By offering a strong refund policy, providers can demonstrate their confidence in their product and their commitment to customer satisfaction, thereby enhancing trust and perceived utility.

In light of these considerations, we propose:

H2: The refund option positively affects the perceived utility of the SaaS lifetime deals.

A lifetime deal in the SaaS context provides access to software services indefinitely. This extended relationship between the consumer and the service provider elevates the role of regular feature updates in the perceived utility of the deal.

Feature updates signify a continuous commitment to improving product quality and user experience, attributes that can significantly enhance the perceived utility for consumers. In a lifetime deal, the expectation of consistent improvement and adaptation to changing technological trends is heightened as the customer's commitment to the service spans an undefined period. Thus, their reliance on the service's ability to stay current and useful over time is amplified (Yang et al., 2015).

Moreover, the lifetime nature of the deals implies a long-term use of the software, increasing the customer's exposure to potential software-related issues or evolving user requirements. Regular updates not only address these concerns but also provide assurance of the software's ongoing adaptation to emerging trends and user needs, thus further amplifying the perceived utility (Waters, 2005).

Innovation, embodied in this case as regular software updates, can enhance customers' perceived utility of a product or service (Simon et al., 2012). By promising regular updates, service providers demonstrate their dedication to staying at the forefront of technological advancements, a characteristic that customers find appealing and which can increase the perceived utility of lifetime deals. Given this, in the context of lifetime deal purchases in the SaaS sector, we propose the following hypothesis:

H3: Feature update positively affects customers' perceived utility of SaaS lifetime deals.

When examining lifetime SaaS deals, the significance of price becomes multifaceted. Customers have to weigh the higher upfront cost of the lifetime deal against the recurring costs of standard subscriptions. This dynamic can have an impact on both the perceived utility and purchase intention towards these deals. The cost of a lifetime deal can equate to only a few years of subscription fees, making it attractive for long-term users and potentially increasing the perceived utility due to anticipated cost savings over time.

On the other hand, the higher initial investment in a lifetime deal introduces an element of financial risk, as the software's future relevancy, the provider's sustainability, and the customer's continued need for the service are uncertain. This perceived risk can reduce the utility of the lifetime deal for the customer, even when they recognize the potential for long-term cost savings (Heart, 2010). This leads us to suggest:

H4: Price negatively affects the customer's perceived utility of SaaS lifetime deals.

Following the evaluation of the utility of a lifetime deal, the customers then consider their purchase intentions. While the long-term cost-effectiveness of a lifetime deal can present high utility, the substantial financial risk associated with the initial investment could deter customers from proceeding with the purchase (Rossignoli et al., 2017).

Yet, if customers perceive high utility in terms of long-term cost-effectiveness, they may be more willing to accept the initial financial risk, consequently increasing their purchase intentions (Zhuang et al., 2010). This outlines the influence of perceived price utility on the intention to purchase, leading us to propose the following:

H5: Utility of price positively affects the customer’s purchase intention of SaaS lifetime deals.

In the complex environment of SaaS products and lifetime deals, various elements can modify the influence of price on purchase intentions. It is recognized in the literature that supplementary features and service enhancements can provide added value to customers, influencing their perception of the utility of the service (Rust et al., 2000). This added value has the potential to moderate the negative impact of price on purchase intention. For instance, offering regular feature updates, as a sign of ongoing innovation and commitment to product improvement, can increase the perceived value of the product and mitigate the deterring effect of high prices. Based on this reasoning, we propose:

H5a: The utility of price on purchase intention is increased in the presence of feature updates.

Moreover, the perceived risk associated with lifetime deals can significantly impact the consumer's willingness to pay. Uncertainty about the product's future development and the sustainability of the provider's business can increase the perceived risk (Tversky et al., 1991). This elevated risk may heighten the price sensitivity of consumers and deter purchase intentions. Hence, we propose:

H5b: The effect of high perceived risk on the purchase intention is lessened as the utility of price gets higher.

The time horizon of product usage can play a crucial role in moderating the effect of price. Consumers who intend to use the service for an extended period are likely to perceive greater value from lifetime deals. As a result, they may be less price-sensitive and more likely to purchase the service despite the higher initial outlay (Nunes et al., 2004). Accordingly, we put forth:

H5c: The effect of a long usage period on the purchase intention is lessened as the utility of price gets higher.

Given the intricate nature of Software as a Service (SaaS) and lifetime deals, perceived risk emerges as a significant factor that impacts purchase intentions. Perceived risk in this context includes concerns about the product's performance, the sustainability of the provider company, and the future usefulness of the service (Bauer, 1960). These risks become integral considerations for consumers as they influence satisfaction and perceived value from the product or service (Peter et al., 1975). Consequently, a heightened sense of perceived risk could reduce the purchase intention of SaaS lifetime deals, as consumers may be reluctant to make a significant financial commitment in the face of uncertainty. This reasoning leads us to our next hypothesis:

H6: Perceived risk is negatively related to the customer’s purchase intention of SaaS lifetime deals.

Moreover, offering a refund option could serve as a mitigating factor against perceived risks. Refund policies can function as a safety net for customers, reducing the perceived risks associated with the transaction (Kukar-Kinney et al., 2003). Under circumstances of high perceived risk, customers may place greater value on this safeguard, which can enhance the utility of the refund option. This, in turn, could positively influence their purchase intention, suggesting a potential moderating effect of refund options on the relationship between perceived risk and purchase intention. Therefore, we propose:

H6a: The negative effect of the high perceived risk on the purchase intention is lessened as the utility of the refund option gets higher.

Trust plays an indispensable role in consumer purchase decisions, particularly in contexts involving significant financial commitment and uncertainty, such as SaaS lifetime deals and it significantly influences a consumer's willingness to depend on the provider in the face of risk (Cho et al., 2015). A high level of trust in a SaaS provider is likely to enhance the purchase intention, as consumers feel more confident about the provider's future conduct, service quality, and fulfillment of promises. Accordingly, we propose the following hypothesis:

H7: Perceived trust is positively related to the customer’s purchase intention of SaaS lifetime deals.

Further, trust can influence how consumers perceive and evaluate other attributes of the offer. For instance, the utility derived from the refund option, which functions as a risk mitigating factor, could be diminished in the presence of high perceived trust. When customers have a high level of trust in a service provider, they feel less apprehensive about potential risks and are less reliant on safeguards such as refund options. Therefore, we propose:

H7a: The effect of the high perceived trust on the purchase intention is lessened as the utility of the refund option gets higher.

The term digital competency refers to an individual's aptitude in effectively employ digital technology (Janssen et al., 2013). This capability holds increasing significance in the context of Software as a Service (SaaS) consumption, particularly when it comes to lifetime deals. Individuals who possess a greater level of digital competency can typically better understand the potential benefits and usage of SaaS offerings, making them more likely to invest in SaaS lifetime deals (He et al., 2021). This propensity could be due to the long-term nature of these deals: with a high level of digital competency, individuals are likely to adapt to any changes, updates, or modifications in the service swiftly over time. Thus, we present the following hypothesis:

H8: Perceived digital competency is positively related to the customer’s purchase intention of SaaS lifetime deals.

Moreover, the influence of digital competency extends beyond direct purchase intention. It also has the potential to be moderated by the utility derived from other attributes of the SaaS offering. For instance, consumers with high digital competency may find less need for human support since they can leverage their skills to solve potential issues or optimally use the service. This implies that the presence of human support might weaken the positive impact of digital competency on purchase intention. In line with this reasoning, we propose:

H8a: The effect of the high digital competency on the purchase intention is lessened as the utility of human support gets higher.

Particularly in the context of lifetime deals, the frequency of usage and the availability of feature upgrades are crucial factors in the Software as a Service (SaaS) environment in determining the purchase intention. Usage frequency refers to how often customers use the SaaS product. High usage rates are a sign that a client depends significantly on the product, such as maybe incorporating it into everyday tasks, and derives a lot of benefit from using it (Hamilton et al., 2011). Thus, the following hypothesis is proposed:

H9: Usage frequency is positively related to the customer’s purchase intention of SaaS lifetime deals.

Offering feature updates, however, may considerably improve the software's perceived value and usability for those who use it frequently. These consumers are likely to enjoy and gain from updates and new features that boost their productivity or user experience since they rely extensively on the tool (Davis, 1989). In this situation, offering feature updates might operate as an effective motivation, making the lifetime deal appealing and so increasing purchase intentions. As a result, it is possible to hypothesize that providing feature upgrades will reinforce the rise in purchase intention if usage frequency is high. Consequently, we propose the following hypothesis:

H9a: The effect of the high usage frequency on the purchase intention is increased as the utility of feature updates gets higher.

The period of usage also plays a pivotal role in shaping customers' purchase intention in the SaaS sector. A longer usage period allows customers to develop a deeper understanding of the service and its benefits, fostering a greater sense of value and satisfaction. This prolonged engagement often leads to stronger customer relationships, higher levels of satisfaction, and ultimately, increased likelihood of purchase (Bhattacherjee, 2001). In line with this, we propose our final hypothesis:

H10: The usage period is positively related to the customer's purchase intention of SaaS lifetime deals.

CHAPTER 4: RESEARCH DESIGN

Following a comprehensive review of the extant literature, we delved into the various factors that could potentially characterize lifetime deals. This exploration was complemented by a focus group study, which aided in the validation of conjoint attributes and levels, with the primary aim of identifying attributes that influence lifetime deal purchase intentions.

This section will subsequently provide a detailed account of our data collection process, as well as an introduction to the variables under consideration. Our methodological approach entailed the utilization of a Mixed Logit model to discover the effects of the key SaaS lifetime attributes on the utility and the application of Hierarchical Bayesian methodology to test the effect of individual level factors together with attribute utilities on the purchase intention.

Further, Confirmatory Factor Analysis (CFA) was employed to derive factor scores, contributing to a more robust understanding of the constructs. The ten-berge method was used to minimize the bias. By applying factor score regression that was found from the CFA & ten-berge method, we test the moderation effect of the utilities of the attributes on the purchase intention in the context of Software-as-a-Service (SaaS) lifetime deals. This comprehensive research design enabled us to explore and understand the complexities of consumer decision-making processes in relation to lifetime deals in the SaaS industry.

4.1. Focus Group Study

A focus group study is an informal discussion with special participants to discuss a certain topic (Becket al. 1986: 73). The focus group study is important because in this way we can understand other perspectives about the topic and get valuable insights before conducting the survey and running the analysis (Wilkinson, S. 1998). In the conjoint analysis, researchers determine the key SaaS lifetime deal attributes to research the topic. By conducting the focus group study, experts give their opinions about the key SaaS lifetime attributes that might affect the utility of the consumer.

The participants of the focus group should carry mutual specialties depending on the topic that will be discussed in the group study. The optimal participant count is between 6 and 12. In order to make the study efficient, the duration of the meeting should be around 1 and a half hours (Wilkinson, S. 1998).

Before the meeting, the researcher prepares the focus group questions (Basch, 1987). The general structure is Ice breaker questions, an introduction to the focus group study, research questions / key questions, closing questions, and thank you part (Morrison-Beedy et al., 2001). After preparing the focus group questions, the researcher determines the participants' profiles that will be suitable for the study (Rabiee, 2004; Redmond et al., 2009). Then the researcher sets the meeting date and books the meeting location for the meeting date. It's critical to obtain an agreed-upon date from the informants well in advance of the interviews and to remind them a few days before they begin in order to maximize participation (Rabiee, 2004). The location should be easily accessible for the participants and be suitable for the meeting settings. There should be a long table with enough chair counts (Rabiee, 2004). The researcher should make sure that the recording device works and gets the voice from every corner of the table properly (Basch, 1987). The researcher sends a reminder email before the meeting date, in this way, the absence is minimized. Providing some snacks and tea/coffee might be helpful to run the meeting efficiently (Basch, 1987).

During the meeting, the first thing the moderator does is greet everyone, introduce the participants and why (and from which perspective) everyone is important for this study, and explain the topic clearly by giving additional background information if it is necessary, and making sure that the participants understand what outcomes are expected from them. The researcher starts to ask questions according to the focus group question structure that was prepared before the meeting (Redmond et al., 2009).

The moderator should encourage participants to express their opinions. There might be some participants who are dominating the meeting, the moderator should control the situation and let everyone speaks for a similar period of time (Redmond et al., 2009).

The moderator should keep the focus on the question that is being discussed at the moment. Some participants might introduce new ideas/concepts outside of the scope of the question and the direction of the meeting might be departed. At that time, the moderator should remind the question again and bring the focus back to the main question (Plummer-D'Amato, 2008).

The moderator can ask further questions that are not in the question structure that was prepared before to dig into the answer of the participants to understand the underlying idea of the comment. Taking notes during the meeting is helpful to jot down important findings.

After the meeting, the researcher listens to the recording a couple of times not to miss any important details and ideas and finalize the outcomes for the continuation of the study (Basch, 1987).

Table 2. Focus group participants

Participant Name	**Age**	**Occupation**	**Why is that person invited?**
U.Y.	40	Entrepreneur & Angel Investor	Experience in founding startups. He prepared a lot of presentations for his businesses. Startup pitch deck, progress report, investor update
E.D.	26	Startup CEO	Experience & expertise in developing software products
A.A.	25	Startup CEO & Marketing Manager	Experience & expertise in assessing product market fit
B.K.	35	Program Coordinator	Evaluater of startup projects including those of software service companies
P.E.	26	Software Product Designer	She designs software products
Y.U.	26	Startup CEO	Experience & expertise in founding startup
E.A.	26	Customer of new startup online presentation software company	She uses a new startup online presentation tool

4.1.1. Focus Group Introduction

The focus group study began with the introduction of the participants.

We then explained the motivation for the research and the research questions. "What key SaaS lifetime attributes may influence consumers' purchase preferences?"

Of course, to be able to discuss which attributes are important, we first prepared a presentation containing two examples to explain what an attribute and level are. The first example was a study about cars. Six attributes related to cars and their levels were shown as examples. The levels were specified as high and low. The second example was outdoor apparel. Attributes and levels related to this product were also displayed. The levels were specific responses to the attribute. Through these two examples, we helped participants understand how attributes can be associated with the product and what the levels could be.

And then, we asked the participants for their initial thoughts. We reminded once again that we are not researching what the participants' buying or not buying preferences would be but what influences consumers' purchase preferences of SaaS lifetime deals.

4.1.2. Discussion of attributes

In the conducted focus group, several themes emerged regarding the key SaaS lifetime attributes influencing consumers' purchase preferences towards a lifetime deal of a product. Participants discussed the importance of several attributes, including price, usability, and the ability to export and integrate with other programs. They also highlighted the value of the product design reflecting contemporary aesthetics and the need for templates based on users' needs.

Participants emphasized the significance of "usage frequency" as a critical attribute, suggesting that consumers are likely to consider how often they would use the product before deciding on a lifetime purchase.

Trust in the company was deemed as another essential factor, with participants expressing concerns about whether the company would continue its services or provide post-purchase support in the long term. The accessibility of presentations across different devices and both online and offline was also highlighted.

The influence of other users' comments and the compatibility of the product's output with other platforms were also noted as critical. Other attributes, such as the program's integration with other software, the presence of how-to guides, customization options, and collaborative features, were considered significant.

The conversation also touched upon data learning capabilities, analytic features, and refund policies, which were all seen as impactful factors. The participants suggested that consumers might consider how many years of price the lifetime fee corresponds to. Offering a discount when recommended to a friend was also viewed as potentially influencing purchase decisions.

Participant U.Y. proposed that cost could be a cardinal determinant in the context of purchasing decisions. Y.U., another participant, emphasized the significance of the export type of the presentation program. He underscored the importance of being able to modify the presentation in alternate programs post-exportation, a viewpoint that received agreement from other participants.

Concurrently, B.K. raised a concern about the potential long-term detrimental impacts of offering a lifetime deal for the company. However, U.Y. reminded the group that the study's perspective was centered on the buyer, not the corporation. The objective was to identify the attributes that significantly influence the utility of SaaS lifetime deals. Reiterating the motivation for the study, the researcher noted the common failure of new startups due to product-market fit issues and inadequate funding. They proposed that companies could mitigate these problems by offering lifetime deals, which could secure substantial upfront funding and valuable feedback. They questioned how services should be designed to entice consumers to accept these lifetime agreements.

As part of the discussion, U.Y. recommended that the design of the presentation should adapt to the era's aesthetics. The participant outlined the evolution of design trends from the early 90s to the present day and expressed that a platform purchased for a lifetime should present designs corresponding to its time, thus introducing the idea of "innovative output".

This perspective was complemented by E.D., who suggested the importance of templates based on user needs. P.E. highlighted the attribute of ease of use and emphasized that frequent usage would elevate the significance of this feature. This line of thought was picked up by A.A., who reinforced the idea of "usage frequency" as a critical feature for lifetime offers.

In the context of lifetime deals, E.D. brought up the subject of "trust," emphasizing the criticality of assuring consumers that the service will persist over time. She voiced potential concerns about a lack of ongoing improvements or support and stressed the importance of trust in the company's long-term viability. Subsequent dialogue underscored the importance of "post-purchase support."

Participants also highlighted the importance of accessing presentations from various devices and in both online and offline modes. P.E. stressed the significance of user testimonials in influencing lifetime purchase decisions, a viewpoint that was unanimously agreed upon by the other participants.

U.Y. underscored the importance of cross-program compatibility, with A.A. and E.D. concurring. In addition, Y.U. and U.Y. discussed the necessity of the presentation program's integration with other applications, and all participants agreed with the assertion of perpetual access to purchased products.

Various other features were suggested, such as "how-to guides" (E.D.), "customizability" and "collaboration" (E.D.), and the importance of company-identity-aligned presentations (A.A.). E.A. proposed the attribute of a learning platform, one that uses user data to present relevant content.

A recurrent theme was the importance of "support," revisited by Y.U., and E.D. proposed the analytical feature as another potential key factor. The researcher introduced features such as "discount/free trial" to stimulate discussion and shift perspective when the flow of attribute ideas seemed to slow.

E.D. highlighted the significance of a "refund" feature, a sentiment agreed upon by the other participants. They suggested that a sufficiently long refund period would allow users to effectively engage with the tool, test it, and see results.

The group concurred that the lifetime fee's correspondence to a certain number of annual fees could be a crucial purchasing criterion. Additionally, P.E. suggested that referral discounts could also influence the perceived utility.

4.1.3. Determining Essential Attributes Affecting Lifetime Purchase Preferences

In a situation where no new attribute ideas emerged, the researcher opened a discussion on which features spoken until then could be identified as the "most important" attributes affecting purchase preferences of SaaS lifetime deals.

The list began with the "price/discount amount" feature. One participant (E.D.) stated that his concern wasn't whether the price was high or low but rather, how his gain compared to the subscription price. Participant U.Y. concurred, noting the importance of the payment period. This individual also highlighted the significance of how quickly he could recoup his investment. B.K. introduced a technical explanation, "return on investment." This was subsequently deemed an essential attribute.

The second item discussed was the "innovation of output." The researcher questioned whether this feature influenced overall purchasing preferences or specifically affected lifetime purchase preferences. Since the participants stated that it affects the "overall purchasing preferences," it was determined that this feature may not be essential.

An argument ensued over the importance of the price attribute for lifetime purchase preferences. B.K. suggested it wasn't an important attribute, which led another participant (Y.U.) to pose a hypothetical situation to reconsider the perspective: if the participant were to make lifetime purchase preferences for a product for their company (technopark), wouldn't they consider the price? B.K. conceded that price might be secondarily important, asserting that quality was more significant. E.D. shared a recent experience of purchasing a lifetime social media management tool for her company, which she returned due to dissatisfaction. She replaced it with another product, regardless of price, which she found satisfactory. She noted, however, that she would have preferred the lifetime product if it had met his expectations, given its price advantage.

Despite B.K. reiterating the insignificance of price, P.E. concurred with the sentiment, asserting that the return on investment, or how much of the product's regular price he could recoup over a given period, might be more significant. Another participant, Y.U., stressed that continuity of use might be more important than price.

When discussions on price started to prolong, the researcher paused this specific discussion to cover other attributes, intending to revisit this topic later for better time management.

E.A. mentioned that while the innovation of output affects all purchase preferences, receiving constant updates significantly affects lifetime deal purchase preferences. U.Y. suggested that if we specifically look at lifetime purchase preferences, the scope, price, trust, and continuity could be the most important features. B.K. argued that the quality, which B.K. emphasized, affected general purchase preferences rather than lifetime purchase preferences. Following this, E.D. reiterated that good and innovative output affects general purchase preferences, but the continuity/sustainability of the output is a significant factor for lifetime purchase preferences.

U.Y. emphasized again that continuity in usage is a more influential feature in lifetime purchase preferences.

The participants collectively agreed that unlimited features could influence the decision to make lifetime purchase preferences.

The participants concurred that the feature of providing purpose-oriented templates influences general purchase preference.

U.Y. reiterated the importance of "Trust" in significantly affecting lifetime preferences. They proposed that lifetime products, due to their long-term nature, must guarantee that the presentations made will never be lost (i.e., any data loss).

When the researcher mentioned the "After-sales customer support" feature, all participants unanimously agreed on its importance. They clarified that while the "Trust" feature answers the question, "Will this company always be around?", the "after-sales customer support" answers the question, "Will I find someone to help when I encounter a problem?" U.Y., referring to a very famous company in Turkey, illustrated how these two features can be distinguished.

It was decided that the feature of "Having feedback channels" could be included in the "after-sales customer support" feature, as feedback is a significant aspect of customer support.

At the end of the session, the participants had a collective consensus on the importance of price, continuity/sustainability of output, trust, after-sales customer support, and return on investment for making lifetime purchase preferences. They noted that while other features might also influence purchasing preferences, these stood out as the most important attributes.

4.1.4. Determining the Levels of Essential Attributes

The researcher introduced a discussion on what the levels of the recently discussed attribute, the "refund policy", could be. E.D. argued that the duration of the refund could be level. B.K. proposed that the deduction rate could be selected as a level, arguing that a refund with a 10% deduction could affect purchasing preference.

As the refund period was being discussed, B.K. asked if there was a legal refund period, and the other participants discussed whether there was a legal period based on their experiences and sectors. Opinions came forward suggesting that the level could be "month" and its multiples rather than "long" or "short". Levels such as "Refund Available" and "No Refund" were also evaluated. It was argued that the refund period should be long enough to experience the service. Final levels were determined as "2 weeks", "1 month", and "2 months", considering existing examples in the software industry.

It was concluded that continuous usage by the user was an important factor. While discussing the levels of this feature, U.Y. stated their opinion by saying, "If I used it for a month, I would not buy a lifetime. It should be long enough". When one participant referred to it as "frequency", other participants corrected the misunderstanding by stating that the feature currently being discussed was not "usage frequency" but "usage duration", and the two were different. U.Y proposed sample levels such as "1 month", "1 year", and "5 years". Other participants later argued that "5 years" was too long and that correcting it to "3 years and above" would better cover the need. Final levels were determined as "less than 3 months", "average 1 year", and "more than 3 years".

It was decided that the "Unlimited Storage" feature could be leveled as "available" and "not available".

Several level types were proposed for the "continuous updates" feature. Firstly, it was suggested that we could label it as "available" and "not available". One participant argued that the period or frequency of updates could also be used as a level. Levels of "not available", "monthly", "annual" were proposed. One participant gave an example, "Let's say we buy PowerPoint 2018, it never updates, updates once a year, or continuously updates", suggesting that the final levels could be "none", "once a year", or "more than once a year". The other participants accepted this suggestion.

One participant proposed that the levels for the "after-sales customer support" feature, considered another essential feature, could be "24/7" and "mail support". Another participant suggested that "easy accessibility" could be accepted as a level, while another participant argued that the "response time" could be used as a level. At this point, there were participants who argued that these levels could also affect general purchase preferences at the same rate but that the presence or absence of it would certainly affect lifetime purchase preference. Another participant E.D insisted that the levels needed to be different by saying, "What affects my lifetime purchase preference a lot would be if I could find a real person when I encounter a problem after making a lifetime purchase because if I subscribe and if I encounter a problem and cannot solve it, I cancel it, but when I buy lifetime, I do not have the chance to cancel so I need to be able to communicate with a real person." E.D proposed that the levels could be "human support" and "bot support", and a consensus was reached on this level.

When the topic of "trust" came up, a participant (A.A.) argued that "upcoming updates" and "customer support" features could be sub-features of "trust". When one participant mentioned that "trust" is a feature that affects general purchasing, another participant (E.D.) articulated that "trust" influences lifetime purchase preferences, stating, "For example, I am significantly affected by whether I will still be able to access this service two years later. I look at its roadmap, the investments it has received, news shared about it, and comments written about it." E.D. emphasized that "trust" is even more critical for lifetime purchase preferences than for general purchase preferences. A.A. strengthened E.D.'s argument by adding, "If it's a subscription, I'll cancel it in case of a problem, but with a lifetime purchase, I don't have this opportunity." While discussions about trust were ongoing, E.D. shared that they scrutinize the website and corporate social media profiles of a product they are going to purchase for a lifetime, stating that this forms a perception of "trust". Ultimately, referring to the strength of their websites and public profiles, it was decided that the levels would be "credible" and "incredible".

The presence of feedback channels was considered an essential feature, but since it was already included in customer support, levels were not reestablished.

The feature of "seeing reviews from lifetime customers" was also incorporated into the "credibility" feature, and levels were not determined for this feature either.

At the end of the study, the discussion returned to the "price" feature. The importance of the user's gain rather than the amount was reiterated in terms of price. Discussions on price lasted for a while. Finally, it was collectively decided to consider it in terms of the "return on investment" period, and its levels were determined as "less than 6 months", "average 1 year", and "more than 3 years".

During our focus group discussions with experts, it became clear that the price, return on investment (ROI), and discount feature were key factors influencing lifetime purchase preferences. Notably, the complexity of incorporating these three features simultaneously due to potential interdependencies led us to focus on one variable - 'price'.

We initially intended to represent the 'price' attribute via ROI options framed as break-even points. These points denoted the time it would take for the lifetime deal to become financially preferable over recurring payments, divided into Low (6 months), Medium (12 months), and High (24 months) categories. However, this approach had its inherent challenges. For one, the concept of a break-even point might not be intuitively comprehensible to survey respondents, potentially impacting the validity of responses.

To mitigate this issue, we consulted with two SaaS industry experts. Their insights, coupled with our review of relevant market research, suggested that directly displaying the price would facilitate clearer comparisons for respondents (Mazar et al., 2016). Thus, the 'price' attribute was structured around three direct price points: $49.99, $99.99, and $149.99.

The "sustainability" feature was also incorporated into the "credibility" feature, and its levels were not determined.

4.1.5. Focus Group Conclusion

After determining the levels of all essential attributes, participants were briefed on how this research would be conducted and thanked for their participation.

One day after the focus group study ended, we sent an email to all participants asking for their additional thoughts on the focus group study and what other factors could influence their lifetime purchase preferences.

In response, the focus group study highlighted the sector known as the "conscious consumer", who seeks "optimal price/performance" regardless of income, attaching importance to this regardless of whether their income is low or high.

"Heavy" presentation software users/presenters, who may try different products with special LTDs for presentation software, were also referred to.

In addition to these:

Income level was presented as a factor which would affect both subscription and lifetime purchase preferences.

Risk aversion was another factor mentioned.

"Technology Enthusiasts", who may prefer LTDs because they tend to use a lot of different "tools", were also brought up.

The view was proposed that demographic characteristics could also affect purchasing preferences.

Final Decision of Researchers on the Features to be Included After the Focus Group Study

After conducting our focus group study, we rigorously compiled the diverse opinions of our expert panel, systematically evaluating each to determine the critical attributes and their corresponding levels.

Among the myriad attributes considered, we opted to emphasize the 'price' attribute, which we categorized into three distinct levels: $49, $99, and $149. This attribute was of significant interest as it offered the opportunity to scrutinize the economic thresholds influencing consumer behavior.

Furthermore, we decided to delve into the 'refund option' attribute, with 'refundable' and 'non-refundable' levels, to grasp a more nuanced understanding of customer risk perception. Complementing this, the 'human support' attribute was chosen, where we evaluated the effects of 'human support' versus 'no human support' on SaaS lifetime purchase preference.

Lastly, the 'feature updates' attribute was pursued, with the level of 'regular feature updates' and 'no feature updates', as an indicator of the customer's willingness to commit to a product based on its potential for growth and improvement.

These selected attributes gained prominence due to their consistent emphasis in both the existing literature and our recent focus group study. Importantly, they surfaced as the prime factors impacting Software as a Service (SaaS) lifetime purchase preferences, thereby justifying our decision to place them at the forefront of our investigation.

4.2. Data Collection

The initial step in our data collection process was the delineation of product attributes and their respective levels. These attributes and levels were necessary for accurately representing the various characteristics of Software as a Service (SaaS) lifetime deals that exist in the real market. Once these aspects were established, we embarked on creating an array of product profiles. Each profile embodied a unique combination of the predefined attributes and levels, representing a potential SaaS offering.

Subsequent to the creation of the product profiles, we undertook the task of designing a custom survey application. The purpose of this application was to present respondents with different product profile comparisons. This was done to ensure we could capture comprehensive insights into how various attributes within SaaS lifetime deals affect perceived utility. Also, in the second section of the survey, we aimed to collect consumer-related variables and to understand the purchase intention of the consumer.

Before launching the main survey, we conducted a pilot study. This crucial step allowed us to test the effectiveness and reliability of the survey and provided an opportunity to make necessary adjustments and improvements based on the feedback and findings from the pilot respondents.

Upon refining the survey design based on the pilot study feedback, the main data collection phase commenced. To attract a wide array of potential respondents, we shared the survey via LinkedIn. To incentivize participation, we offered an Amazon gift card as a reward. We stressed that participation was voluntary, and we assured all respondents that their data would be treated with the utmost confidentiality.

The final stage in the data collection process was data cleaning. We meticulously reviewed the collected data to identify and filter out random or inconsistent choices. This cleaning step significantly improved the overall quality and reliability of our dataset. By strictly adhering to this comprehensive process, from defining attributes and levels, creating product profiles, conducting a pilot study, deploying the refined survey, to cleaning the collected data, we ensured the robustness of the dataset. This dataset, in turn, served as a solid foundation for the testing of our research hypotheses.

4.2.1. Pilot Study

Subsequent to the development of the survey design, a preliminary pilot test was conducted within a small representative cohort comprising 20 individuals. The purpose of this initial test was to identify and rectify potential areas of confusion, as well as detect any problematic elements within the survey's design or presentation. This represents a common step in survey research to ensure the tool's comprehensibility, functionality, and overall reliability prior to large-scale implementation (Van Teijlingen et al., 2002).

Following the pilot test, participant feedback highlighted a few issues, most notably concerning the control variable where the same question was asked three times. The repetition appeared to introduce confusion among the respondents. In response to this feedback, modifications were made to the survey design to improve its clarity and cohesiveness.

With the necessary adjustments made in the post-pilot test, the survey was deemed ready for full-scale implementation. Thus, the pilot test played an instrumental role in enhancing the survey's efficacy, contributing to the validity and integrity of the data to be collected in the larger study. This process illustrates the commitment to academic rigor and reliability in this research endeavor.

Ensuring Data Integrity in Survey Implementation

In our research endeavor, we implemented numerous measures to ensure the validity and reliability of our data. To foster meaningful engagement from participants and mitigate the impact of random or unconsidered responses, we utilized several strategies.

Firstly, our conjoint analysis was structured to include more than the standard binary choice (Product A or Product B). Instead, we provided a nuanced spectrum of options: 'Definitely Product A', 'Product A', 'None', 'Product B', and 'Definitely Product B'. This approach allowed us to capture a broader range of participant preferences, enhancing the richness and granularity of our data.

We employed three strong filters to ensure the validity and reliability of the collected data. The first filter applied was a timing threshold. Based on repeated trials, we established a minimum survey completion duration of 3 minutes and 10 seconds. Consequently, we excluded all responses completed in less than 2 minutes to maintain data quality and ensure that respondents have spent adequate time considering each question.

We aimed to mitigate response bias, particularly the tendency for respondents to repeatedly choose the same option, such as "Definitely Product A" for every comparison. By using the second filter, we removed the responses of respondents displaying this pattern.

The third filter involved comparisons where one option was objectively superior to the other. In these instances, if a respondent selected the inferior option, it raised concerns about the respondent's understanding or attentiveness to the task. Consequently, we decided to remove all responses from such respondents to maintain the integrity of the data. This comprehensive filtering process helped in enhancing the reliability and validity of our data, and by extension, the findings derived from it.

To underline the seriousness and purpose of the survey, we emphasized its academic nature at the outset. Additionally, we offered an Amazon gift card as an incentive for participation, while clearly stating that random or inauthentic responses would lead to exclusion from this offer. This balanced the goal of encouraging participation with the necessity of maintaining data integrity.

Furthermore, we appealed to the empathy of participants by sharing our financial constraints. We hypothesized that this emotional appeal might foster a more engaged and considerate response, reducing the occurrence of random or disengaged answers.

A crucial concern was the potential for multiple submissions from the same participant. To counteract this, we developed a custom survey application that inserted a temporary cookie into each participant's device upon initial engagement with the survey. This cookie served to uniquely identify the device from which the participant was accessing the survey. In the event of a repeat submission attempt from the same device, our system recognized the existing cookie and subsequently blocked the additional submission.

This preventative measure, coupled with our strategies to minimize random responses, ensured the integrity and authenticity of our data. Our methodological approach underscores our commitment to maintaining the highest standards of academic research, and our belief in the value of robust, reliable data as a foundation for meaningful insights and conclusions.

A bespoke survey application was developed for the purpose of this research, with the primary impetus being the need for dynamic, real-time customization of respondent experience. This strategy marked a divergence from the use of generic survey applications, principally due to the requirement of presenting a unique set of 10 pairwise comparisons to each respondent upon survey initiation.

Each respondent was systematically assigned a unique ID upon survey activation. This unique ID facilitated the generation and presentation of a personalized set of 10 pairwise comparisons for each respondent.

The survey itself was segmented into two principal sections, subsequent to an initial introduction that outlined the survey information and explained Amazon gift card rules.

The first section was purposed for the presentation of the pairwise comparisons, wherein each respondent was presented with 10 sets of product profile comparisons, eliciting their preference for each pair.

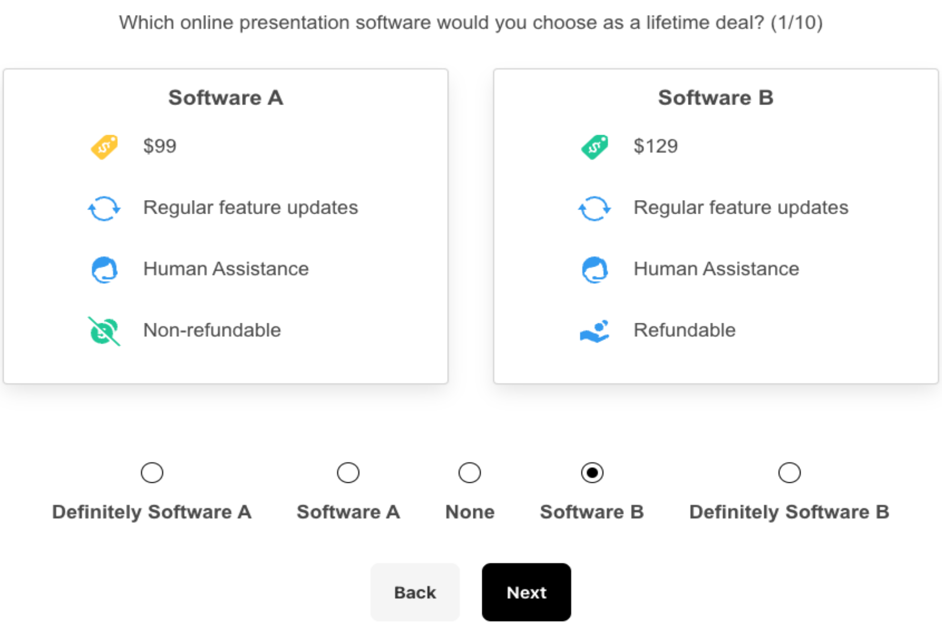

Figure 4. A scenario of lifetime deals with different attributes.

The completion of these 10 comparisons triggered the initiation of the second section. This section comprised a series of questions formulated on a Likert scale, targeting the capture of a range of perceptual constructs.

The first query in this section served as a control variable, the nature of which was determined in line with the primary research objectives. This was followed by a series of questions aimed at eliciting respondent perceptions of risk, trust, and digital competence. These questions sought to capture the nuances of individual perceptions and beliefs that might bear upon their choices in the first section of the survey.

In the concluding part of this second section, demographic data were collected from the respondents. These data provided the means to control for various demographic factors in subsequent analyses and enabled a more nuanced understanding of how demographic characteristics might intersect with product preferences and perceptions of risk, trust, and digital competence.

Finally, to encourage participation and enhance respondent engagement, respondents were offered an optional opportunity to enter into an Amazon gift card raffle. To facilitate this, with their consent, respondents were requested to provide their email addresses at the end of the survey.

The development and use of a custom-built survey application ensured the alignment of the data collection process with the specific requirements of our choice-based conjoint analysis, perceptual evaluations, and demographic analyses. This tailored approach promoted a more nuanced capture of respondent preferences and perceptions, bolstering the robustness of our empirical study.

4.2.2. Variables

In this study, four key attributes were identified, each with distinct levels:

Table 3. Attributes and Levels

Attribute	**Level 1**	**Level 2**	**Level 3**
Price	$49	$99	$149
Refund	Refundable	Non-refundable	
Feature Updates	Regular feature updates	No feature update	
Support	Human assistance	No human assistance	

These attributes and their corresponding levels, in total, generated 24 potential product profiles (3x2x2x2=24):

Table 4. Profiles

Profile ID	Price	New Feature	Customer Support	Refund
1	$49	No feature update	No human support	Non-refundable
2	$99	No feature update	No human support	Non-refundable
3	$129	No feature update	No human support	Non-refundable
4	$49	Regular feature updates	No human support	Non-refundable
5	$99	Regular feature updates	No human support	Non-refundable
6	$129	Regular feature updates	No human support	Non-refundable
7	$49	No feature update	Human support	Non-refundable
8	$99	No feature update	Human support	Non-refundable
9	$129	No feature update	Human support	Non-refundable
10	$49	Regular feature updates	Human support	Non-refundable
11	$99	Regular feature updates	Human support	Non-refundable
12	$129	Regular feature updates	Human support	Non-refundable
13	$49	No feature update	No human support	Refundable

Table 4 (Continued). Profiles

14	$99	No feature update	No human support	Refundable
15	$129	No feature update	No human support	Refundable
16	$49	Regular feature updates	No human support	Refundable
17	$99	Regular feature updates	No human support	Refundable
18	$129	Regular feature updates	No human support	Refundable
19	$49	No feature update	Human support	Refundable
20	$99	No feature update	Human support	Refundable
21	$129	No feature update	Human support	Refundable
22	$49	Regular feature updates	Human support	Refundable
23	$99	Regular feature updates	Human support	Refundable
24	$129	Regular feature updates	Human support	Refundable

In a full factorial design, where every possible combination is presented for comparison, the number of required pairwise comparisons would be calculated using the binomial coefficient formula (often referred to as 'n choose 2'.):

$C(n, 2) = n! / [2!(n-2)!]$

where:

n! represents the factorial of n, which is the product of all positive integers up to n.

k! is the factorial of k.

(n-k)! is the factorial of (n-k).

This formula calculates the number of ways a subset of 2 elements (representing the two profiles being compared) can be drawn from a larger set of n elements (the total number of profiles). In our study, the total number of profiles (n) was 24. Thus, the number of pairwise comparisons required for a full factorial design would be C(24, 2) = [24! / (2!(24-2)!)] = 276 comparisons.

However, such a significant number of comparisons presents a considerable cognitive load for respondents and risks inducing fatigue and nonresponse bias, which could adversely impact the reliability and validity of the data.

In our case, we randomly generated product profiles for each respondent. Every respondent saw 10 comparisons, selected a subset of 20 profiles from the original 24 profiles.

This revised design was administered to a sample of 2195 respondents, ensuring sufficient data for robust statistical analysis while optimizing the respondent experience and completion rates.

4.2.3. Consumer-Related Variables

In the present study, we are embarking on an empirical exploration that incorporates conjoint analysis and a triadic set of measurement instruments (Perceived Risk, Perceived Trust (Verhagen et al., 2006) and Perceived Digital Competence (OECD, 2015) to examine consumer behavior. Our intent is to capture the complex interplay between individual consumer characteristics and the perception of attribute partworth utility scores, a measure used to identify the relative importance of different product attributes in influencing consumers' decisions.

By enhancing our understanding of these determinants, we anticipate a more nuanced interpretation of consumer decision-making processes, thereby contributing to the extant literature on consumer behavior and shaping strategies for effective market engagement.

Table 5. Consumer-Related Variables

Variables	Scale	Item	Scale item
Purchase Intention (Yi, 1990)	7-point Likert scale	PI_1	Improbability
		PI_2	Likebility
		PI_3	Possibility
Perceived Risk (Verhagen et al., 2006)	7-point Likert scale	PR_1	As I consider purchasing a lifetime deal from a new startup company, I become concerned about whether the company will commit fraud.
		PR_2	As I consider purchasing a lifetime deal from a new startup company, I become concerned about whether the company will swindle (cheat).
		PR_3	As I consider purchasing a lifetime deal from a new startup company, I become concerned about whether the company offers software products that will not perform as expected.
		PR_4	As I consider purchasing a lifetime deal from a new startup company, I become concerned about whether the company will behave opportunistic.
Perceived Trust (Verhagen et al., 2006)	7-point Likert scale	PT_1	New startup companies are in general dependable.
		PT_2	New startup companies are in general reliable.
		PT_3	New startup companies are in general honest.
		PT_4	New startup companies are in general trustworthy.

Table 5 (Continued). Consumer-Related Variables

Perceived Digital Competence (OECD, 2015)	4-point Likert scale	$PICT_1$	I feel comfortable using digital devices that I am less familiar with.
		$PICT_2$	If my friends and family want to buy new digital devices or applications, I can give them advice.
		$PICT_3$	I feel comfortable using my digital devices at home.
		$PICT_4$	When I encounter problems with digital devices, I feel I can solve them.
		$PICT_5$	If my friends and family have a problem with digital devices, I can help them.
The frequency of using an online presentation tool	No-scale, 5 distinct choices	UFR	Never, Rarely, Sometimes, Usually, Always
The expectancy to use an online presentation tool for a long time	No-scale, 2 distinct choices	UPR	No, Yes

We have incorporated personal questions as a significant component of our research methodology. The inclusion of these questions serves a dual purpose: firstly, it enriches our dataset with a variety of demographic factors, and secondly, it allows us to explore potential relationships between these personal characteristics and attribute partworth values.

This approach is underpinned by the premise that demographic factors may influence perceptions of attribute partworth, thereby potentially affecting consumer decision-making processes. By systematically examining these relationships, our research seeks to contribute to a more nuanced understanding of how personal characteristics may intersect with attribute partworth evaluations in the context of consumer behavior. This approach aligns with our broader goal of generating insights that have both theoretical and practical relevance.

Table 6. Control Variables

Variables
Gender
Education
Monthly household income
Age
Country

4.2.4. Dependent Variable

In the pursuit of our research, our dependent variable is the lifetime deal purchase intention. The statement describing this dependent variable reads as follows: "My purchasing an online software presentation tool with a lifetime offer is…". This assertion acts as an indicator of respondents' preferences towards the long-term commitment of such a purchase.

We have utilized a seven-point Likert scale to measure responses to this statement, thereby providing a nuanced spectrum of potential attitudes. Such a scale enables the collection of ordinal data, from which we can extract meaningful insights about the attitudes, opinions, and behaviors of our respondents (Yi, 1990).

This ordinal scale ranges from one extreme to another, bracketing a spectrum of neutral to strong feelings about the statement. By including this dependent variable in our research, we are able to measure the purchase intention of each individual participants.

4.3. Sample Profile

A total of 2195 complete responses were retained for data analysis. The general rule of thumb for conjoint analysis is to have a minimum of 200–300 completed surveys; thus, a sample size of 2195 was found to be acceptable (Orme, 2006). The sample profiles are presented in Table 7.

Table 7. Sample Profiles

	N=2195
Gender	
Male	59.77%
Female	38.31%
Prefer not to say	1.91%
Education	
Primary school	0.09%
Elementary school	2.14%
High school	11.44%
Bachelor's Degree	56.90%
Master's Degree	25.51%
Ph.D. Degree	3.92%
Household income	
Less than $500	0.50%
$501 – $2.000	5.74%
$2.001 – $3.500	26.97%
$3.501 – $5.000	41.05%
Over $5.000	25.51%
Prefer not to say (skip)	0.23%

Table 7 (Continued). Sample Profiles

Usage period	
Long	86.10%
Short	13.90%
Usage frequency	
Never	0.36%
Rarely	6.38%
Sometimes	35.22%
Usually	46.47%
Always	11.57%

4.4. Experimental Design

Experimental design, also known as the design of experiments (DOE), is a statistical methodology that aids in systematic planning, conducting, and analyzing the results of an experiment to extrapolate accurate and objective conclusions (Vaux et al., 2012). It serves as a cornerstone in scientific studies to ensure the efficacy of experiments, minimize variability, and increase the reliability of results. The principal aim of an experimental design is to obtain insight into causal-effect relationships by mitigating bias and controlling for known and unknown variables (Montgomery, 2017).

Key aspects that are intrinsic to an effective experimental design are:

Randomization: This is the procedure of randomly allocating experimental units across different treatment groups to ensure that the experimental conditions do not favor a particular group. Randomization assists in mitigating systematic error and facilitates an unbiased inference (Fisher, 1935).

In our study, we randomized all pair-wise comparisons and assigned random respondent IDs to every 10 pair-wise comparisons. Then, assigned the respondent ID to the respondent randomly.

Replication: This denotes the act of repeating the entire experiment on multiple experimental units to mitigate random error and increase the precision of estimated effects (Casler, 2015).

Blocking: This involves separating experimental units into homogeneous blocks or groups that are exposed to the same conditions, thereby reducing the effect of known sources of variability (Montgomery, 2017).

4.5. Choice-Based Conjoint (CBC) Analysis

Choice-Based Conjoint (CBC) Analysis is a multivariate statistical technique that falls within the broader spectrum of Conjoint Analysis, a technique widely employed in marketing research (Agarwal et al., 2014). Its primary function is to analyze consumer preferences by deducing the underlying value system that governs their choices.

In CBC Analysis, respondents are presented with an assortment of hypothetical product/service profiles, each comprising a unique combination of different attribute levels, and asked to indicate their preferences or make choices (Train, 2009). For instance, in the context of a car, attributes could include power, fuel efficiency, appearance, gadgets, safety, price, etc., with each attribute featuring varying levels.

The subsequent data derived from these choices facilitates the calculation of the relative importance of each attribute level. This quantification of consumers' decision-making processes serves to inform design decisions, pricing strategies, and marketing strategies in a comprehensive manner (Louviere et al., 2000).

Key strengths of CBC include:

Reflects Real-World Decision-Making: CBC emulates real-life consumer decision-making processes, demanding respondents to make trade-offs across attributes, thereby providing a realistic gauge of consumer preferences (Agarwal et al., 2014).

Estimates Interactions Between Attributes: CBC is equipped to estimate the interaction effects between different attributes, unveiling the influence of one attribute on the perceived value of another (Train, 2009).

Determines the Importance of Price: CBC can isolate and quantify the role price plays in a consumer's decision-making process by comparing it against the influence of other product attributes (Louviere et al., 2000).

Notwithstanding these advantages, CBC demands complex design and analysis and requires respondents to engage in cognitively hard trade-off exercises. Despite potential challenges, its strengths substantiate its standing as a powerful tool in marketing research, fostering a deep understanding of consumer decision-making (Agarwal et al., 2014).

Part-worth utility

Part-worth utility, also referred to as attribute-level utility, is a fundamental concept in conjoint analysis. In conjoint analysis, consumers' product preferences are assessed based on the product's attributes, each of which contributes to the overall utility or value of a product. The part-worth utility represents the contribution of a specific level of an attribute to the overall utility of a product (Green et al., 1990). A higher part-worth utility implies a higher level of preference for that attribute level.

4.6. Mixed Logit Model

In our research design, we employed a statistical technique known as the Mixed Logit model (Hensher et al., 2003) to derive utility estimates for various attributes. This advanced model allows for a deeper understanding of consumer preferences by permitting random variation across consumers and correlations among alternatives.

It is important to clarify that the utility estimates derived through this method do not represent individual-level preferences. Instead, they reflect the general utilities associated with the attributes under investigation. Consequently, the Mixed Logit model does not provide individual-specific beta coefficients, presenting a potential limitation, particularly in light of the individual-level responses we have collected.

Due to this characteristic of the model, our dependent variable in this phase of the analysis is not the individual purchase intention but the aggregate utility estimates. These estimates, nevertheless, enable us to discern which attributes significantly influence consumer preference and to what extent. For instance, we can ascertain whether a price point of $99 substantially affects the perceived utility of the product.

It is crucial to underscore, however, that while utility can be hypothesized to influence purchase intention, our application of the Mixed Logit model does not verify this relationship. The model's purpose is to identify the attributes' general utilities, not to establish a direct causal link between utility and purchase intention. Such linkages will be explored and validated in subsequent stages of our research.

4.7. Hierarchical Bayes Multinominal Logit

To ascertain individual-level purchase intentions, we implemented a statistical approach known as Hierarchical Bayes Multinomial Logit (HB MNL) (Gelman et al., 2003). The HB MNL is an advanced method that accommodates the heterogeneity of individual-level data, overcoming the limitations presented by the Mixed Logit model.

The HB MNL model operates by estimating the posterior distribution based on prior estimations. It conducts this process iteratively, running the model numerous times (in our case, 1000 iterations) to refine the estimations of beta coefficients. This iterative process facilitates the generation of individual-specific beta coefficients, which can provide granular insights into individual preferences and purchase intentions.

Upon deriving these individual-level beta coefficients for each attribute (i.e., price, feature update, refund, and human support), they are treated as observations that allow us to identify and profile the respondents. These beta coefficients are then merged with the respondent ID dataset, aligning the estimated preferences with the corresponding individual.

4.8. Confirmatory Factor Analysis

In the next stage of our research design, we employed Confirmatory Factor Analysis (CFA), a multivariate statistical procedure that is used to test how well-measured variables represent the number of constructs. For this analysis, we drew upon four distinct question sets concerning perceived risk, perceived trust, perceived digital competence, and a control variable centered on online software purchasing intention.

Each set comprised multiple questions, specifically, three for the purchase intention, four each for perceived risk and perceived trust and five for perceived digital competence. The essence of using CFA is to consolidate the responses from these multiple questions into a single score for each set.

The rationale behind using multiple questions per set was to mitigate the potential for measurement error. Each question within a set essentially measures the same construct but from slightly different perspectives. If we were to ask only a single question per construct, it could potentially lead to misunderstandings and misinterpretations by the respondents, thereby introducing errors. By asking 4-5 similar questions for each set, we reduce the possibility of such measurement errors.

The application of CFA further enhances the robustness of our approach. Through CFA, we confirm that the questions within each set accurately represent the intended construct. The resulting scores from CFA for each set, therefore, provide a more reliable and accurate measure of the constructs of interest, namely perceived risk, perceived trust, perceived digital competence, and the control variable related to purchasing behavior.

4.9. Factor Score Regression

In the last phase of our research design, we used Factor Score Regression Analysis, a powerful statistical method that allows us to examine the relationship between variables.

In the context of our research, the use of Factor Score Regression Analysis was pivotal in connecting the utilities derived from the Mixed Logit model and the individual-level purchase intentions extracted via the Hierarchical Bayes Multinomial Logit. It also allowed us to incorporate the results of the Confirmatory Factor Analysis, in which we derived consolidated scores for perceived risk, perceived trust, and perceived digital competence, along with a control variable. We used ten-Berge estimation to mitigate biases on the critical correlations between factors (Logan et al., 2021).

By integrating these varied elements into a regression model, we were able to quantify the influence of these factors on the consumer's purchase intention towards SaaS lifetime deals. Specifically, we could ascertain how much of the variation in purchase intention can be explained by the variation in these factors. This analysis is instrumental in understanding which attributes significantly impact purchase intention and thus offers valuable insights for strategies aimed at enhancing the attractiveness of SaaS lifetime deals.

CHAPTER 5: RESULTS

Our research sought to explore the various factors affecting customers' utility and purchase intentions when procuring SaaS lifetime deals.

5.1. Mixed Logit Results

In accordance with our hypotheses (H1, H2, H3, H4), as seen in Table 8, we found that the provision of human support, refund options, and feature updates positively influenced the perceived utility of a product. On the contrary, the price had a negative impact on utility.

Table 8. The effects of the attributes on the utility

Coefficients:

	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept):2	0.083313	0.017696	4.708	2.50E-06	***
Price $99	-0.275101	0.02974	-9.2502	< 2.2e-16	***
Price $129	-0.431674	0.030707	-14.0578	< 2.2e-16	***
Feature Update	0.801326	0.028787	27.8362	< 2.2e-16	***
Human Support	0.647022	0.027083	23.8903	< 2.2e-16	***
Refund	0.866092	0.029168	29.693	< 2.2e-16	***
sd.Price$99	0.17675	0.085448	2.0685	0.03859	*
sd.Price$199	0.525669	0.062512	8.4091	< 2.2e-16	***
Feature Update	0.868207	0.051384	16.8963	< 2.2e-16	***
Human Support	0.684824	0.051188	13.3786	< 2.2e-16	***
Refund	0.829544	0.049752	16.6736	< 2.2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log-Likelihood: -12190

McFadden R^2: 0.11538

Likelihood ratio test : chisq = 3179.9 (p.value = < 2.22e-16)

5.2. Confirmatory Factor Analysis (CFA) Results

The CFA analysis shows that the research model fits the data well. In the upper summary we see that the Bentler Comparative Fit Index (CFI) is 0.974. If CFI is close to 1 and greater than 0.90, then the model fits very well. Furthermore, we see that the Tucker-Lewis Index is close to 1 which indicates a good model fit. Also, residuals are close to zero (RMSEA=0.040 and SRMR=0.024), it indicates a good model fit.

Table 9. CFA Results

Estimator	ML
Optimization method	NLMINB
Number of model parameters	46
Number of observations	2173
Model Test User Model:	
Test statistc	556.528
Degrees of freedom	125
P-value (Chi-square)	0.000
Model Test Baseline Model:	
Test statistic	16552.463
Degrees of freedom	153
P-value	0.000
User Model versus Baseline Model:	
Comparative Fit Index (CFI)	0.974
Tucker-Lewis Index (TLI)	0.968
Loglikelihood and Information Criteria:	
Loglikelihood user model (H0)	-48577.497
Loglikelihood unrestricted model (H1)	-48299.233
Akaike (AIC)	97246.995
Bayesian (BIC)	97508.453
Sample-size adjusted Bayesian (SABIC)	97362.304
Root Mean Square Error of Approximation:	
RMSEA	0.040

Table 9 (Continued). CFA Results

90 Percent conficence interval - lower	0.037
90 Percent confidence interval - upper	0.043
P-value H_0: RMSEA <= 0.050	1.000
P-value H_0: RMSEA >= 0.080	0.000
Standardized Root Mean Square Residual:	
SRMR	0.024
Parameter Estimates:	
Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:						
	Estimate	Std.Err	z-value	P(|z|)	Std.lv	Std.all
Purchase Intention =~						
PI_1	0.872	0.027	32.055	0.000	0.872	0.689
PI_2	0.961	0.027	35.219	0.000	0.961	0.752
PI_3	0.946	0.027	35.248	0.000	0.946	0.753
Perceived Risk =~						
PR_1	1.008	0.024	41.226	0.000	1.008	0.780
PR_2	1.009	0.025	40.721	0.000	1.009	0.773
PR_3	0.989	0.025	40.867	0.000	0.989	0.775
PR_4	0.982	0.025	39.160	0.000	0.982	0.752
Perceived Trust =~						
PT_1	1.017	0.025	40.352	0.000	1.017	0.768
PT_2	1.043	0.025	41.526	0.000	1.043	0.784
PT_3	1.037	0.026	40.280	0.000	1.037	0.767
PT_4	0.995	0.026	38.669	0.000	0.995	0.745
Perceived ICT =~						
$PICT_1$	0.425	0.019	22.563	0.000	0.425	0.511
$PICT_2$	0.506	0.017	29.680	0.000	0.506	0.646

Table 9 (Continued). CFA Results

$PICT_3$	0.463	0.017	27.485	0.000	0.463	0.606
$PICT_4$	0.459	0.016	28.291	0.000	0.459	0.621
$PICT_5$	0.403	0.016	24.987	0.000	0.403	0.559
Price =~						
Price99	0.354	0.037	9.538	0.000	0.354	0.721
Price129	0.810	0.083	9.785	0.000	0.810	1.169

After finding the estimates of the consumer-related variables (purchase intention, perceived trust, perceived risk, perceived digital competency) and the utility of the price, we used the ten-Benge method to mitigate the bias, and we got the factor scores.

5.3. Factor Score Regression Results

When turning our attention to purchase intentions, however, the picture became more complex. In Table 10 we show the effects of the consumer-related variables on the purchase intention and the moderating effects of the key SaaS lifetime attributes on the consumer-related variables towards SaaS lifetime deal purchase intention.

Table 10. Direct and moderator effects of the factors on the purchase intention

Coefficients					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	-0.222155	0.078189	-2.841	0.004536	**
Price	0.074642	0.055204	1.352	0.176477	
Perceived Risk	0.033656	0.032698	1.029	0.303455	
Feature Update	0.02597	0.045548	0.57	0.568628	
Usage Period	0.133629	0.058074	2.301	0.021486	*
Refund	0.025	0.04255	0.588	0.556896	
Perceived Trust	0.233795	0.033116	7.06	2.24E-12	***
Usage Frequency	0.252392	0.026532	9.513	< 2e-16	***
Human Support	-0.029759	0.051888	-0.574	0.566347	
Percieved ICT	0.151028	0.02669	5.659	1.73E-08	***
Gender Male	-0.01889	0.039149	-0.483	0.629489	
Gender No to say	0.49874	0.138935	3.59	0.000338	***

Table 10 (Continued). Direct and moderator effects of the factors on the purchase intention

Education.L	-0.062822	0.048046	-1.308	0.191171	
Education.Q	-0.024053	0.032745	-0.735	0.462685	
Income.L	0.414547	0.173855	2.384	0.017191	*
Income.Q	-0.105682	0.145539	-0.726	0.467829	
Income.C	0.055197	0.099641	0.554	0.579663	
Income^4	0.017223	0.05714	0.301	0.76313	
Birth Year	0.015513	0.004923	3.151	0.001648	**
Price:Perceived Risk	-0.041594	0.02077	-2.003	0.045345	*
Price: Feature Update	0.049174	0.023623	2.082	0.037493	*
Price: Usage Period	-0.045699	0.058841	-0.777	0.437452	
Perceived Risk: Refund	0.038858	0.038437	1.011	0.312159	
Refund: Perceived Trust	-0.106286	0.036694	-2.897	0.003811	**
Feature Update: Usage Frequency	0.108467	0.026801	4.047	5.37E-05	***
Human Support: Perceived ICT	-0.036159	0.029863	-1.211	0.226095	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1					
Residual standard error: 0.8679 on 2147 degrees of freedom					
Multiple R-squared: 0.2555, Adjusted R-squared: 0.2468					
F-statistic: 29.47 on 25 and 2147 DF, p-value: < 2.2e-16					

We applied grand mean centering to be able to measure the individual effects of the moderating factors separately.

Contrary to expectations, price, perceived risk, feature updates, refund options, and human support did not strongly influence purchase intention. Interestingly, perceived digital competency didn't moderate the effect of human support on purchase intention as we had initially hypothesized. Similarly, contrary to H6a, the perceived risk did not moderate the effect of the refund option on purchase intention, and in line with our results, the usage period did not moderate the effect of price on purchase intention as stated in H5c.

On a nuanced note, usage period was found to have a slight influence on purchase intention, while perceived trust, usage frequency, and perceived competency had a significant impact on it. As H7a proposes, perceived trust negatively moderated the effect of the refund option on purchase intention, which supports the initial expectation in H7a. Importantly, our results demonstrated interesting moderating effects: while perceived risk intensified the negative effect of price on purchase intention, the presence of feature updates could decrease this adverse impact, which is in line with H5a and partially supports H5b. Additionally, usage frequency strongly moderated the effect of feature updates on purchase intention, validating H9a.

Table 11. Discriminant Validity Test

	Prc.Int.	Prcv.R	Prcv.T	Prcv.ICT	Price
Purchase Intention	1.000				
Perceived Risk	0.359	1.000			
Perceived Trust	0.390	0.796	1.000		
Perceived ICT	0.374	0.641	0.662	1.000	
Price	0.013	0.077	0.016	0.066	1.000

Discriminant Validity tests were performed to assess the distinctiveness of the constructs in our model. Table 11 showcases that each construct is indeed distinct from the others. This was determined by the HTMT ratio of each construct. If the HTMT value is less than 0.85, it indicates that the construct captures more variance from its indicators rather than from other constructs, supporting discriminant validity.

The Average Variance Extracted (AVE) scores illustrate the amount of variance that is captured by a construct relative to the amount due to measurement error. A construct with an AVE score above 0.5 suggests that the construct explains over 50% of the variance of its indicators, signifying acceptable convergent validity. Our AVE scores greater than 0.5 show satisfactory values for all constructs, implying that our indicators appropriately represent their respective constructs.

The reliability analysis show that our constructs are reliable, where Cronbach's alpha values for all constructs are shown to exceed 0.7. A Cronbach's alpha above this threshold indicates a high level of internal consistency among the indicators, suggesting that the items measure the same underlying construct, therefore providing reliable results.

The Composite Reliability scores similarly assess the internal consistency of the indicators forming each construct, similar to Cronbach's alpha, but taking into account the different loadings of the indicators. All our constructs demonstrated a composite reliability score well above the acceptable 0.7 thresholds, providing further support for the reliability of our constructs.

Finally, our multicollinearity test results ascertain that our model does not suffer from multicollinearity issues. Multicollinearity can obscure the individual effects of predictors. Our Generalized Variance Inflation Factor (GVIF) values for all variables are below the typical cutoff of 5, implying that our predictors are not overly correlated, and the regression coefficients should be stable and interpretable.

In summary, while several of our hypotheses were supported, others were not corroborated by our findings. These results highlight the intricacies and complexities of understanding customer behaviors in the context of purchasing SaaS lifetime deals and suggest avenues for further research.

CHAPTER 6: CONCLUSION

This research sheds light on the significant financial challenges startups, particularly those in the SaaS market, frequently grapple with. Offering lifetime deals emerges as a potent strategy that secures an initial user base, provides an upfront revenue stream, and creates a potential competitive edge against more established brands. However, it also presents risks to consumers, given the significant upfront commitment. Thus, understanding the critical factors affecting consumers' purchase preferences in lifetime deals is pivotal to optimizing these deals' benefits and mitigating associated risks.

The research was structured around two comprehensive models. The first examined the effects of key SaaS lifetime attributes—price, human support, refund option, and regular feature updates—on consumer utility. The second delved into the effects of consumer-related variables —perceived risk, trust, digital competency, usage frequency, and period— on purchase intention, investigating the moderating effects of the utility of the key SaaS lifetime attributes on these relationships.

Various methodologies were employed to ensure robust results. Following an in-depth literature review and a focus group study with experts, the key SaaS lifetime attributes and the level of these attributes were determined. After that, a pilot study refined the survey instrument by getting feedback from pilot survey respondents. Amazon gift cards was offered to incentivize survey participation as well as securing the data quality. The final survey collected data from a wide participant pool, with 2195 responses deemed appropriate for analysis after filtering random answers by using various filtering methods.

The research utilized a mixed logit model, revealing that all investigated attributes significantly impacted consumer utility. A hierarchical Bayesian model was used to find the individual-level coefficients. After that, confirmatory factor analysis (CFA) was used to find the estimate of the consumer-related variables and the utility of price. By using the ten-Berge method, the bias was minimized. After getting the factor scores from the CFA and ten-Berge method, a factor score regression was used to uncover the impact of consumer-related variables on purchase intention and how the utility of the key SaaS lifetime attributes moderated this.

On the purchase intention side, the study found that usage period, perceived trust, usage frequency, and digital competency all had significant positive effects on purchase intention. Control variables such as gender, age, and income were also found to be significant. Additionally, the utility of price was discovered to negatively influence the effect of perceived risk and positively affect the effect of feature updates on purchase intention. Furthermore, the utility of the refund option negatively influenced the effect of perceived trust on purchase intention, while the utility of feature updates positively influenced the effect of usage frequency on purchase intention.

In conclusion, this extensive study unravels crucial aspects of consumers' decision-making processes regarding SaaS lifetime deals. It highlights that all the examined key SaaS lifetime attributes significantly impact consumer utility, and the utility of the key SaaS attributes moderates the effect of the specific consumer-related variables on the purchase intention. These insights significantly enhance understanding of consumer purchase preferences in the SaaS lifetime deal context, providing startups with a valuable model to strategically navigate lifetime deals. This approach is poised to boost their competitiveness and provide financial support for long-term success.

6.1. Theoretical Implications

Our research endeavored to provide a holistic understanding of the factors influencing the perceived utility and purchase intention of SaaS lifetime deals. The analysis revealed a detailed portrait of consumer behavior, validating some hypotheses while compelling us to reconsider others.

For instance, the key SaaS lifetime attributes, such as price, feature updates, refund options, and human support, had a significant effect on perceived utility, conforming to our expectations. However, the utilities of the attributes did not directly influence purchase intention. This finding suggests that the utility of the key SaaS lifetime attributes moderated the effect of the consumer-related variables on purchase intention.

Additionally, our study shed light on the critical role consumer-related variables play in shaping purchase intention. Usage period, perceived trust, usage frequency, and digital competency emerged as strong positive influencers of purchase intention.

However, the relationships were not as straightforward as they might seem due to the moderating effects of the utilities of certain attributes.

For instance, the utility of price had a negative moderating effect on the perceived risk of purchase intention. This suggests that when consumers perceive high utility from price (likely due to perceived value-for-money), the deterrent effect of perceived risk on purchase intention diminishes. In contrast, the utility of price had a positive moderating effect on the feature updates on the purchase intention, suggesting that a perceived value-for-money heightens the positive impact of feature updates on purchase intention.

The utility of the refund option had a negative moderating effect on the perceived trust in the purchase intention. This result hints at a possible perception among consumers that a high utility refund option, perhaps seen as a safety net, lessens the need for trust when deciding to purchase.

Lastly, the utility of feature updates positively moderated the effect of usage frequency on purchase intention. This demonstrates the symbiotic relationship between regular feature updates and usage frequency, where frequent users derive more value from regular updates, thereby increasing their propensity to purchase.

Interestingly, we did not find support for the hypothesis that the utility of human support would negatively moderate the positive effect of digital competency on purchase intention. It suggests that even with high digital competency, consumers still value human support, underscoring the intrinsic complexity of the relationship.

In summary, while our research significantly contributes to understanding consumer behavior in the SaaS industry, particularly regarding lifetime deals, the complexity and multifaceted nature of this behavior point towards avenues for future research. By delineating the direct of the key SaaS lifetime attributes on perceived utility, the moderating effects of the attributes on purchase intention, and the direct effects of the consumer-related variables on the purchase intention, this research provides a refined lens to view the dynamics of consumer decision-making in the SaaS market.

6.2. Methodological Contribution

In considering the methodological contribution of our research, it is clear that our study presents a novel application in the relatively underexplored domain of choice-based conjoint analysis. A majority of existing studies utilize rating-based conjoint analyses, whereby each profile is rated and subsequently analyzed through regression techniques. Alternatively, researchers conduct choice-based regressions, bifurcating the samples based on differentiating factors (for instance, groups with high and low perceived risk), followed by the application of various models to ascertain significant differences.

However, our methodology deviates from these conventional approaches, amalgamating the strengths of Mixed Logit model, Hierarchical Bayes Multinomial Logit, Confirmatory Factor Analysis, and Regression Analysis. We employed a comprehensive approach that not only takes into account the utilities of different attributes but also individual-level purchase intentions and aggregated scores for key constructs.

This innovative methodological approach has not been widely employed in choice-based conjoint analyses, marking it as a significant contribution to the methodological discourse in this domain. Our study demonstrates the potential of this methodological fusion in providing in-depth and nuanced insights, thereby advancing the field's methodological sophistication.

6.3. Managerial Implications

Our findings provide several critical implications for managers and stakeholders in the SaaS industry. Firstly, features such as human support, feature updates, and refund options significantly influence the perceived utility of a SaaS lifetime deal. Thus, SaaS providers, especially startups, should consider investing in these areas to increase the perceived value of their offerings.

The influence of perceived trust, digital competency, usage frequency, and usage period on purchase intention underscores the importance of building strong relationships with customers. Companies should aim to foster trust, perhaps through transparent communication and reliable service delivery. Likewise, facilitating the development of users' digital competency (e.g., through tutorials or online resources) could enhance their confidence in using the product, possibly boosting sales.

Additionally, our results suggest that while the utility of the price doesn't have a significant direct influence on purchase intention, it does interact with other factors such as perceived risk and usage period. Therefore, pricing strategies should be carefully considered, taking into account the target market's risk perception and expected usage duration.

6.4. Limitations & Future Research Avenues

While this study has provided valuable insights, several areas warrant further exploration. It might be beneficial to investigate why certain factors (like the utility of the price and perceived risk) don't significantly influence purchase intention in the SaaS lifetime deal context. Is this a peculiarity of the SaaS industry, or does it reflect broader changes in consumer behavior? Also, exploring why certain moderating effects were not found (e.g., between perceived digital competency and the utility of human support) could provide deeper insights into the interplay between these factors.

Future research could also seek to validate our findings in different contexts - for instance, across different SaaS categories, in various geographical locations, or at different price points. As consumer behavior can be influenced by numerous external factors, these additional investigations would help confirm the generalizability of our results.

Lastly, it would be interesting to explore other potential influencers of SaaS purchase intentions, such as brand reputation, social influence, or specific product features. Such research could further enrich our understanding of consumer behavior in the SaaS industry and provide even more nuanced insights for practitioners.

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