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INFORMACIJOS ASIMETRIJOS ĮTAKA KAINODAROS STRATEGIJOMS MOBILIŲJŲ PROGRAMĖLIŲ RINKOJE	**THE INFLUENCE OF INFORMATION ASYMMETRY ON PRICING STRATEGIES IN THE MOBILE APPLICATIONS MARKET**

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1. INTRODUCTION

The Challenge of Uncertainty in the Saturated Mobile Applications Economy. The digital economy has changed the principles of commerce, and this shift is nowhere more visible than in the mobile applications market. Over the past decade, the mobile app economy has grown from a new technology into a massive global industry. Recent industry reports indicate that consumer spending on in-app purchases across Apple's App Store and Google Play reached $150 billion in 2024, which is a 13% increase from the previous year. Regarding the new download numbers, they held steady at approximately 136 billion (Sensor Tower, 2025). Therefore, these industry reports indicate that the mobile market is growing significantly. However, this massive growth has created a challenging paradox: it has never been easier for market entrants to launch a new app. Still, it has become even harder to build a successful application. The vast array of applications available across the market has created a potential discoverability crisis, where even high-quality applications are likely to go unseen. As noted by mobile analytics company Adjust (2024), the challenge is not one of app volume but also one of structural fragmentation: user attention is divided across diverse digital channels, such as mobile, PC, and Connected TV. This essentially makes the user acquisition more complex than previously. In such a disjointed ecosystem, the ability to capture instant user attention is no longer just a marketing advantage; it is also about an application's survival.

In this crowded application environment, one of the main frictions is information asymmetry. Mobile applications are essentially experience goods, for which you often cannot tell whether an application is good, useful, or safe until a user has downloaded and used it for a while (Ghose & Han, 2014; Nelson, 1970). This essentially creates a digital version of Akerlof's (1970) "Market For Lemons". The problem is not just about quality, as Smith (2019) points out, but also extends to data security. Users typically lack the technical skills to audit an application before installing it. It essentially means that the user might be uncertain about both the utility of the application and personal data security. Therefore, Consumers must rely on proxies such as icons, names, descriptions, and ratings, which might not accurately reflect an application's actual value.

From the Developer's point of view, this creates a strategic dilemma. If the consumers cannot trust the product before they purchase it, they will not pay upfront. Momenzadeh and Camp (2017) argue that without clear signals of quality, the market would inevitably shift toward lower quality options. Therefore, the choice of monetisation strategy – Paid, Ad-Supported, Freemium or Hybrid – is not only about maximising the revenue potential, but it has become more of a strategic move to manage the trust gap between the developer and the user, which serves as a first and most important signal in the developer's confidence in their own product.

Relevance of the Topic. This matters quite significantly now, because the industry is moving away from the legacy and the choice of offering a Paid vs Free monetization model. The market is increasingly becoming dominated by the Hybrid model, which combines both free access, by monetising through ads, and premium options through In-App Purchases (hereinafter – IAP). This evolution suggests that in the volatile modern digital market, there is no single revenue model sufficient for application developers.

This shift has shown that the spillover effects of digital goods are recognised by the app developers. Deng et al. (2023) note that free users are valuable not only for ad revenue but also for the network effects and social proof they generate. This indirectly helps to attract and monetize paying users. The dominance of the Hybrid model also suggests that developers are trying to capture the whole market by monetizing users' time through ads and users' purchases through IAPs. By diversifying these revenue streams, developers are employing a strategy within the application that protects against potential risks from ad rate fluctuations or decreases in consumer purchasing power.

Understanding this dynamic is key for both theory and practice. In practice, failures of mobile startups often occur between the product and its business model – for instance, trying to sell a paid application without enough social proof and reputation to justify the upfront cost. In the academic literature, examining this relationship is also critical, as it connects the concept of market signalling with the changing nature of business models in the mobile application industry (Roma & Ragaglia, 2016). It shifts the focus from achieving revenue goals for developers to understanding the necessary survival strategies in a dynamic and uncertain mobile market environment.

The Research Gap. While existing research provides a solid foundation, there is a missing piece in the puzzle regarding how information asymmetry impacts the choice of strategy. Previous studies, such as those by Mayzlin et al. (2014), examine how reviews act as signals, but they also warn about the signal-jamming phenomenon, as reviews may be manipulated. Thus, users are assessing more signals before purchasing or downloading an application, rather than relying solely on reviews. Smith (2019) expands on this problem by arguing that information asymmetry in the application market concerns not only functional quality but also data security. Thus, the low-quality application problem requires more credible signals than the user reviews alone.

Roma and Ragaglia (2016) established that revenue models drive financial performance. However, the literature still lacks a comprehensive understanding of why developers choose specific pricing and how these choices relate to their initial informational standing. Recent work by Deng et al. (2023) highlights the spillover effects of freemium models, showing how free users generate value for the paid version. However, this research largely assumes that the developer has the agency to strategically select the model that maximizes these spillovers. It does not fully address the limitations faced by new entrants, who often lack the necessary signals to pursue a paid strategy.

This thesis would shift the focus to the supply side. The primary gap in current research is that pricing is usually treated as a flexible tool to influence demand. This was exemplified by Ghose and Han (2014), who focused on estimating consumer price elasticities rather than on the developer's initial strategic choice. Also, Roma and Ragaglia (2016), in their literature review, have criticized the field for focusing on the impact of price on performance metrics, such as downloads or rank, rather than on the drivers of the strategy itself. Therefore, the literature has not yet focused on a different element, such as how the lack of information signals would force a developer to choose their monetization strategy. For a new entrant, pricing may be less of a choice and more of a structural constraint. For instance, if a developer has a sparse description, no website, and no rating history, would they effectively be forced into an ad-supported model simply because they cannot convince users to pay an upfront cost to acquire the application.

Moreover, while most of the literature prioritizes revenue maximization, revenue stability is arguably more critical for long-term survival in a market (Momenzadeh & Camp, 2017). There is little empirical evidence that would indicate which monetization strategies would help to stabilize the user base over time. By overlooking the role of uncertainty mitigation, current studies fail to explain why some lower-revenue strategies might be preferred by developers who value longevity and stability over short-term profits.

The Research Question. Theories of information asymmetry (Akerlof, 1970) and the subsequent development of signalling and screening models (Spence, 1973; Stiglitz & Weiss, 1981) have provided a foundational framework for understanding strategic interactions under uncertainty. However, the mobile application ecosystem has presented unique challenges to these established theories. As literature explores, signal jamming could be prevalent in the mobile app world, while it might lead to numerous fake reviews and increase information asymmetry between developers and consumers (Mayzlin et al., 2014). In an environment where social proof can be fabricated, pricing strategies emerge as a critical and credible mechanism to mitigate potential information asymmetry between developers and consumers (Deng et al., 2023). Yet, while pricing can act as a signal, the causal link between the selection and efficacy of these pricing strategies remains unclear. Therefore, it is necessary to understand how specific information asymmetry determines the initial choice of pricing strategy (supply-side decision) and how effective these models are at resolving the market uncertainty (demand-side decision). Therefore, by bridging the gap between strategic choice and market stability, the following research questions are raised:

Research Question 1 (RQ1): How do varying degrees of information asymmetry between mobile application developers and consumers impact the selection of different pricing models within the mobile application marketplace?

Research Question 2 (RQ2): To what extent can the implementation of specific monetization strategies mitigate market uncertainty and enhance revenue stability for mobile application developers?

The Research Methodology. As for the methodology, for the first research question, Multinomial Logit (MNL) regression will be employed. This would help to analyse what would be the probability of a developer choosing a specific pricing strategy (i.e., Paid, Ad-Supported, Freemium, Truly Free) compared to the market-dominant Hybrid baseline, based on how much of an information asymmetry they are facing, for instance, how new they are, and how many ratings they have. Two models will be made, one for the iOS ecosystem and the other for the Android ecosystem.

As for the second research question, an Ordinary Least Squares (OLS) Regression model would be constructed. In this model, the rating count would serve as a proxy for stable market adoption. This would help measure whether specific monetization strategies are better at building a stable user base and thus ensuring revenue stability for an application and its developers.

The Use of Artificial Intelligence (hereinafter – AI). During the preparation of this thesis, AI tools, like Gemini served as a supplementary tool to improve clarity, refine the logical flow of the arguments and improve overall academic phrasing and coherence of the text. Additionally, Grammarly tool was also used to check for grammatical accuracy and sentence clarity

Hypothesis and Expected Contributions. Based on Signalling Theory (Spence, 1973), this thesis propose that a developer's monetization choice is a direct function of their ability to signal trust

Regarding Strategy Selection, it is anticipated that developers with weak signals will be structurally forced to avoid pricing friction. Therefore, the following hypotheses are proposed:

H_{1a}: Higher degrees of information asymmetry (indicated by shorter descriptions, lack of website, low ratings, and volume) are more likely to be positively associated with Ad-supported and Truly Free models, as developers are lowering the entry barriers and trying to mitigate the consumer risk

H_{1b}: Strong signalling capabilities (high ratings, recent updates, longer descriptions) will be positively associated with Paid and Freemium models, as these signals effectively reduce the information gap, allowing developers to capture more value

Given market uncertainty, the strategy itself may determine the product's revenue stability. Thus, the following hypothesis is proposed:

H_2: Mobile applications that utilize free-to-download monetization strategies (Freemium, Ad-supported, and Truly Free) will have significantly higher rating counts compared to Paid applications.

In short, this thesis investigates the impact of the causal chain between information deficits and strategic choices. By combining Smith's (2019) concerns regarding security signalling with Deng et al. (2023) insights on strategic spillovers, this research aims to explain not only which model performs best, but why the developers are driven to choose them in the first place.

2. LITERATURE REVIEW: INFORMATION ASYMMETRY, PRICING MODELS AND THE ECONOMY OF MOBILE APPLICATIONS

2.1 Concept of Information Asymmetry and Its Economic Consequences

The concept of information asymmetry describes a common market situation in which one party to a transaction has more or better information than the other. The foundation of modern economic analysis of asymmetric information in the markets was set by the contributions of George Akerlof, Michael Spence, and Joseph Stiglitz. For their contributions, they were awarded the Nobel Prize in Economic Sciences in 2001 (Nobel Prize Foundation, 2001). Their research was mainly done during the 1970s; however, it has significantly challenged the neoclassical assumption that information in markets is perfect and symmetric. Akerlof (1970), Spence (1973), and Stiglitz (Rotschild & Stiglitz, 1976; Stiglitz & Weiss, 1981) have demonstrated that an imbalance in information between parties that are transacting is not just a minor friction but is among the central drivers of market outcomes. They have shown that information asymmetry is capable of leading to significant inefficiencies and even to market failures.

2.1.1 Akerlof and Adverse Selection: The ‘Market for Lemons’

Researchers in the current days are still analysing the effect of the information asymmetry. For instance, Weber et al. (2024) are analysing the information asymmetry in the context of Artificial intelligence. However, the core theory of information asymmetry was first described by the economist Akerlof (1970) in his seminal paper "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism". Within the paper, Akerlof (1970) has used an intuitive example of the market for used cars to demonstrate how uncertainty about the quality of the product can systematically weaken the market. The core problem within the used car market lies in an information asymmetry: sellers of used cars have superior knowledge of their vehicle’s quality, while potential buyers do not. Before buying a vehicle, a potential buyer struggles to differentiate a well-maintained and high-quality car from a defective one – “lemon” (Akerlof, 1970)

When faced with such uncertainty, a potential rational buyer will only be willing to pay a price that reflects the average quality of all cars available in the market (Akerlof, 1970). This single, average price is creating a critical dilemma. For an individual who owns a “lemon,” this price is likely to be above their vehicle’s actual value, which would provide a strong incentive to sell. On the other hand, from the owners of a good quality car perspective, this singular average price is likely to be below the car's actual worth. This would discourage the rational seller from participating in the market, since the sale of their car would not be profitable (Akerlof, 1970).

This dynamic sets up a vicious circle, known as adverse selection. This phenomenon occurs when an information asymmetry leads to a market outcome, where "bad" quality products or customers are pushing out the superior ones from the market (Akerlof, 1970; Stiglitz & Weiss, 1981). Since owners of high-quality cars are exiting the market, the average quality of the remaining vehicles in the market is dropping inevitably. As the average quality in the market is deteriorating, buyers are adjusting their willingness to pay as well. Going further, this might also lead to the owners of medium-quality properties to exit the market as well, thus further degrading the market. Going further, its most extreme form, as per Akerlof (1970), not-so-bad quality cars would push out from the market, medium quality cars, and then bad quality vehicles would push out not-so-bad quality cars. This would eventually lead to complete market collapse, where no transactions are occurring for any cars above the lowest quality, as owners of decent quality cars are not willing to sell their vehicles at the lowest possible prices (Akerlof, 1970). Akerlof (1970) also argued that information asymmetry can fundamentally undermine market mechanisms themselves and prevent mutually beneficial trades. Subsequent empirical work, such as Finkelstein and Poterba (2004) has confirmed the presence of these frictions in insurance markets. This concept might be directly applicable to the mobile app market, where quality is highly variable and difficult for users to ascertain before downloading and engaging with an application.

However, even though Akerlof's theory presents this information asymmetry, which might lead to adverse selection and market failure, Grossman and Stiglitz (1980) have introduced a paradox, which argues that perfectly informationally efficient markets cannot exist. This comes from the fact that if prices fully cover all available information, no rational agent would be incentivized to gather it. Without this motivation, trading activity would diminish, ultimately leading to market collapse. Therefore, markets should sustain some "equilibrium inefficiency", where some mispricing remains, so informed traders would be compensated for their information acquisition, allowing for ongoing price discovery (Grossman & Stiglitz, 1980).

2.1.2 Spence and Signalling: Credibly Conveying Private Information

While Akerlof has identified the key problem with adverse selection and information asymmetry, Michael Spence's (1973) work, "Job Market Signaling," has provided a theoretical framework for informed parties on how to actively try to solve it (Spence, 1973). The Spence model analyzes how people can reliably share their private information with other uninformed parties through observable actions, or in other words, signals (Spence, 1973). He saw the hiring process as an "investment under uncertainty" for employers, since they cannot observe an applicant's productivity before hiring (Spence, 1973).

In context, education usually signals ability. The critical part of Spence's theory is that for a signal to be effective, it must be costly, and this cost must be negatively correlated with the unobservable attribute being signalled (Spence, 1973). In the job market, the cost of education not only incorporates the tuition, but it also includes opportunity cost, time spent studying, and the psychological effort. The key assumption is that it is less expensive for a highly productive individual to achieve a certain level of education, compared to someone with low productivity (Spence, 1973)

The key difference in cost is what gives the signal its real informational worth. For less capable workers, it is too difficult and more expensive to achieve the same educational level, compared to highly capable and productive ones. Thus, employers can depend on educational qualifications as a trustworthy signal for productivity (Spence, 1973). This allows the market to reach a separating equilibrium, where different types of workers can self-select into different educational paths and thus signal their private information to employers. Therefore, the key takeaway from Spence's work is that education is valuable not from a perspective that it teaches new skills or improves productivity, but because it stands as a credible signal for employers (Spence, 1973). This concept of a costly, credible signal is essential to understand how mobile app developers, as the informed party, might use various marketing tactics, like A/B testing, and strategic moves to signal the unobservable quality of their product to potential users. For instance, such concepts as an application's quality are signalled through pricing (Danilchik, 2025) or through users' ratings and downloads (Deng et al., 2023).

2.1.3 Stiglitz and Screening: Inducing Information Revelation

While Spence focused on how informed parties are signalling, Stiglitz's research looked at the other side: how uninformed parties can create mechanisms to sort or screen the informed parties to reveal their private information (Stiglitz & Weiss, 1981). This concept is demonstrated in Stiglitz and Weiss's (1981) paper "Credit Rationing in Markets with Imperfect Information".

Stiglitz and Weiss (1981) have challenged the basic economic idea that prices always will rise to clear excess demand. For instance, in the insurance markets, once insurers cannot distinguish between low-risk and high-risk individuals, they set premiums based on average risk. Thus, that discourages low-risk customers from participating in the market and leads to a market dominated by high-risk customers, increasing overall costs and reducing market efficiency (Rothschild & Stiglitz, 1976). Similarly, in the loan market, the lender, who is the uninformed party, has transactions with a group of borrowers, who are the informed parties, where each has different levels of project risks. Therefore, similarly to the insurance markets, lenders cannot distinguish between safe and risky borrowers (Stiglitz & Weiss, 1981). A logical response to excess demand for loans would be to increase the interest rate. However, the interest rate itself acts as a screening device, and increasing it might reduce the quality of the applicant pool.

As interest rates are increasing, the safest borrowers, with the low-risk projects, who are likely to pay back, are leaving the market. The high cost of borrowing basically makes their projects unprofitable (Stiglitz & Weiss, 1981). On the other hand, high-risk borrowers usually are more willing to accept higher interest rates, because they might gain significantly if their projects succeed. If the project would fail, their losses would be limited by bankruptcy, or by limited liability (Stiglitz & Weiss, 1981; Berardi, 2007). This would lead to an adverse selection effect, where a higher interest rate would worsen the average risk of the loan applicants, which might also decrease expected return for the banks (Stiglitz & Weiss, 1981).

As a result, a bank, which is looking to maximize profits, might choose not to raise interest rates to the level that would clear the market. Instead, for the banks, it might be better to keep interest rates lower and ration credit. This would mean that banks might deny loans to some borrowers who would be willing to repay the credit at the current rate or even a higher one (Stiglitz & Weiss, 1981). By setting the terms of a contract, like interest rate and collateral requirements, the uninformed lender would design a mechanism that encourages borrowers to self-sort, effectively filtering out the highest-risk applicants. This concept of screening provides a framework to analyse how uninformed parties, such as app store platforms or even end users, might design or interpret market mechanisms to get information from other informed parties, like developers.

2.1.4 Delegation under Information Asymmetry: The Principal-Agent Problem

Building upon foundational theories of information asymmetry, the principal-agent problem has emerged as a framework to analyse scenarios where one party (or the "principal") delegates a task to another party (or the "agent") (Ross, 1973). The problem in general is driven by two main issues, which often come together: conflicting goals and asymmetric information. Firstly, the principal and agent might have different initiatives. For instance, company owners (principals) are aiming to maximize their profits, while the managers in the firm (agents) might prefer an easier workload or more company perks. This conflict of different interests is difficult to solve because of the second issue: information asymmetry. The agent will always have more information about their action and level of effort than the principal can observe (Jensen & Meckling, 1976). Thus, this framework applies broader concepts of information economics to the specific challenges of managing contracts and delegation.

Within the relationship between the principal and agent, this general problem of asymmetric information gives rise to two specific challenges: adverse selection and moral hazard. Adverse selection is an issue of "hidden information" that might occur before a contract is signed, where the principal cannot evaluate the agent's actual abilities properly, or their type. On the contrary, the moral hazard is described as a problem of "hidden action" that appears only after the contract is in place, as the principal cannot perfectly monitor its decisions or its level of effort (Arrow, 1985; Holmström, 1979). These challenges are giving the creation of "Agency costs", which Jensen and Meckling (1976) have identified as the sum of monitoring costs for the principal, bonding costs for the agent to signal reliability, and the unavoidable residual costs from remaining conflicts of interest. Therefore, a primary cost of agency theory is to address this inefficiency by designing smarter contracts. In other words, mechanisms like performance-based incentives, which would be aimed to minimize total agency costs by more closely aligning the agent's motivations with the principal's objectives (Grossman & Hart, 1983).

2.1.5 Evolution of Information Asymmetry Theory

The combined works of Akerlof, Spence, and Stiglitz offer much more than just separate theories. It essentially maps out a dynamic and strategic interplay of action and reaction in markets, with asymmetric and imperfect information. This progression may be interpreted as an escalating competition for informational advantage. Akerlof (1970) was the first to establish the foundation and identify a market failure, which comes from informational asymmetry and passive uncertainty. Spence (1973) then demonstrated that the informed party might not remain passive, as they might actively attempt to overcome potential market failures by sending credible signals. Stiglitz and Weiss (1981) then showed that even the uninformed party might be a strategic player by developing counterstrategies, like screening mechanisms, to protect themselves and extract information. This dynamic view suggests that any informationally asymmetric market is not static. It should be expected to see an ongoing evolution of strategies and counterstrategies, as market participants are learning and adapting.

The Information asymmetry as a concept remains relevant with the emergence of new digital technologies, such as Artificial Intelligence (hereinafter - AI) and its implementation into various business sectors. For instance, given the recent implementation of AI tools in the finance industry, Weber et al (2024) examine Explainable Artificial Intelligence (hereinafter - XAI) as a tool to increase transparency on how AI solves complex algorithms. It is suggested that XAI is set to decrease information asymmetry between the AI user and the AI tool by providing information on inner mechanisms and how the AI tool works. Thus, that increases the transparency of the AI tool and might lead to higher adoption rates.

2.1.6 Information Asymmetry Within the Digital Platforms

Interest in information asymmetry theory has been driven by the expansion of digital markets and other complex global challenges in recent years. One of the primary areas of evolution is its application to digital and platform economies. The rise of digital platforms like Uber, Airbnb, and even the Apple App Store is essentially establishing markets that are shaped by information asymmetry. Even though these platforms initially were aimed at reducing the informational asymmetry between service providers and end users, they are introducing new imbalances. This mainly stems from the fact that the platforms themselves are becoming a central repository of information, essentially knowing more about market conditions, consumer behaviour, and provider performance than any other market participant. (Dermawan et al. 2020). This relationship creates a principal-agent problem, because platforms (principals) can leverage its information to structure the market in a way, that they would maximize their own revenue, which might conflict with the goals of users (agents) who are seeking for best possible service, or with providers who are seeking to maximize their sales.

To manage the information asymmetries about the digital platforms, they universally employ online reputation systems. While theoretically, it is a direct application of signalling theory, which is designed to solve the "lemons" problem (Akerlof, 1970; Spence, 1973), research suggests that they are still imperfect due to strategic manipulation. Actors tend to engage in practices like posting fake reviews or so-called "signal jamming", which might lead to information pollution, reintroduce adverse selection, and might leave consumers unable to distinguish a genuinely high-quality provider from a clever manipulator (Mayzlin et al., Dover, & Chevalier, 2014; Dellarocas, 2003). Beyond deliberate manipulation, due to the natural cognitive limits of consumers, the volume of authentic data might lead to information overload, thus preventing optimal decision making (Kajtazi, 2011). This might also to focus only on the average star rating, while ignoring nuanced ad often more valuable information within the text of the rereview. Finally, these issues might lead further to the "reputation inflation", where average ratings tend to cluster at the high or low end of the scale, thus devaluing the worth of signal and compromising system's effectiveness in evaluating provider performance (Nosko

& Tadelis, 2015). Ultimately, the mechanism designed to tackle information asymmetry and build trust paradoxically increases scepticism.

2.1.7 Market Consequences and Solutions for Information Asymmetry

When information asymmetry exists, markets can become highly inefficient, leading to various negative consequences. One of the most severe ones is market failure, where the imbalance of power might become so significant that markets would effectively cease to function for certain goods or even collapse entirely, as demonstrated by Akerlof's lemons model (Akerlof, 1970). Yet even when avoiding complete market failure, the constant uncertainty and mistrust created by asymmetric information can significantly reduce transaction volume, even though they might be beneficial to both parties. This might even result in inefficient allocation of resources and a net welfare loss for society, as both consumer and producer surplus are diminished (Einav et al., 2007).

These consequences are driven by two distinct, but related problems: **Adverse Selection** and **Moral Hazard.**

Adverse Selection. As indicated before, this is a problem of hidden information that arises before the contract is signed or the transaction occurs. The uninformed party is unable to identify the type of informed party, thus risking making a poor selection. The examples might include such cases as an insurance company selling a policy to a high-risk individual at a price that was meant for a low-risk individual, or a consumer buying a low-quality product ("Lemon"), which might be disguised as a high-quality one (Akerlof, 1970; Rothschild & Stiglitz, 1976).

Moral Hazard. This is a problem of hidden action that arises after the contract has been signed. It occurs when one party, protected from the full consequences of their actions, might start behaving in a much riskier manner than they would have before. An example could be an individual with flood insurance, who, after buying the insurance, would stop making flood prevention precautions (Stiglitz & Weiss, 1981; Bloomenthal, 2024)

2.1.8 Mitigating Mechanisms: Market-Based and Institutional Solutions

In response to the problems indicated above, both the market itself and regulatory institutions provide relevant solutions to reduce information asymmetry. The existence of these costly solutions is strong evidence of the severity of the underlying imbalance in information.

Market-based solutions should be seen as voluntary mechanisms arising from market participants' incentives to facilitate trade. These include many mechanisms, such as Warranties and guarantees, Reputation and brand name, Low and High Prices, signals, and many others.

Warranties and guarantees. By offering a warranty or a money-back guarantee, a seller of a higher-quality product can signal their confidence in the product's quality and assume some of the buyer's risk. This is a costly signal, as it might incur costs in the future, and it has a high risk of being abused by buyers who are careless in using the product. However, because this signal is costly, sellers of low-quality products would not be willing to offer it. As a result, it would be easier for buyers to distinguish between low- and high-quality goods (Kirmani & Rao, 2000).

Reputation and Brand Name. Through investments in advertising and building up a reputable brand name, sellers might build up a credible reputation for their product. Thus, a strong reputation might also serve as a credible signal to customers, as they learn to trust the quality of the brand's products. The investments in brand image are publicly visible, and costs are incurred before the product is sold. And unlike warranties and guarantees, this signal is not subject to potential abuse of the customer (Kirmani & Rao, 2000).

Low and High Prices. Both high and low prices can strategically be used as a signal for a product's unobservable quality. A low introductory price or coupons may signal a product's high quality by representing a short-term loss for a firm. However, a high-quality firm usually anticipates covering this loss through recurring, higher price purchases later. This strategy would not be profitable for a low-quality firm, whereas their product might not generate customer quality. However, this concept might be subject to abuse by potential customers. On the contrary, a high price can signal superior product quality. This strategy targets quality-sensitive buyers who are willing to pay a premium and will continue to purchase if the quality is verified. This strategy is possible for a high-quality firm, as it might secure profitability. In contrast, a low-quality firm might not secure recurring purchases and would lose the price-sensitive segment of the market (Kirmani & Rao, 2000).

Different forms of financing. To address the issue, where lenders cannot correctly distinguish low-risk individuals from high-risk individuals before providing a loan (Stiglitz & Weiss, 1981), Meki and Quinn (2024) have provided a potential solution with the concept of micro equity – a form of financing, where repayments depend on the performance of the SME. Micro equity contracts are set to reduce the information gap by aligning the interests of lenders and borrowers through performance-based repayment, thus reducing adverse selection risk.

Third Party Certification and Information Intermediaries. Third-party certification and information intermediaries' function by providing credible information or even certification to reduce consumers' uncertainty and asymmetric information. These intermediaries might invest in expertise by certifying or endorsing high-quality goods, thus providing credible signals for consumers (Bisglaiser, 1993). The forms of these signals are diverse, acting as expert certifiers who build and stake their own reputations to advocate for the quality of the product (Biglaiser, 1993; Dranove & Jin, 2010). In the digital era, information intermediaries can be exemplified through online platforms that create reputation systems by providing an electronic word-of-mouth mechanism through user reviews and ratings (Dellarocas, 2003). Even though they may have drawbacks, as discussed before, these systems can reduce user uncertainty and help buyers make more informed decisions before purchasing, thereby reducing information asymmetry (Dellarocas, 2003).

While market-based solutions address information asymmetry, a Keynesian perspective would argue that this mechanism is insufficient, as private markets can fail to coordinate effectively (Keynes, 1936). Therefore, the potential for persistent market failure driven by information gaps might justify government intervention and provide some institutional solutions to reduce information asymmetry:

Regulation and Mandatory Disclosure. Governments might combat information asymmetry by enforcing laws requiring firms to disclose critical information, so investors and consumers can make more informed decisions. For instance, securities laws require public companies to disclose their financial health, which is essential to reduce investors' risk and make capital markets more efficient (Healy & Palepu, 2001). This approach is necessary because, in most cases, relying solely on voluntarily disclosed information is insufficient. This is because most managers do not have an incentive to reveal all the information, due to fears of litigation or potential strategic risk in revealing it to competitors. By compelling disclosure of information, these regulations usually help reduce firms' capital costs and improve market liquidity. Also, it mitigates the fundamental economic frictions that may arise from the information asymmetry (Healy & Palepu, 2001).

Licensing and Certification. In markets where the quality of service providers is difficult for consumers to judge, market-based solutions, such as third-party certification or information intermediaries, might not be sufficient. Therefore, government-imposed licensing might be needed to ensure a minimum level of competence or quality, especially in fields such as medicine or law. This licensing might directly prevent scenarios in which unqualified providers drive skilled professionals out of the market (Leland, 1979). By creating a floor for quality, licensing should allow customers to trust the legitimacy of any certified seller or service provider. However, the key challenge in designing these regulations is to craft them to provide public protection without simultaneously becoming a tool for current professionals to restrict competition and inflate their own prices (Kleiner, 2006). Even recent research has intensified this concern, providing evidence that the rapid expansion of licensing across various occupations might significantly reduce employment opportunities and increase consumer costs, with only a slight improvement in service quality. For example, a comprehensive study by Klee (2022) found that licensing restrictions may disproportionately affect lower-income workers and limit the interstate mobility of professionals. This suggests that in many sectors, the economic costs of licensing outweigh the public benefits (Klee, 2022).

These solutions, whether market-based or imposed by the government, might be effective in reducing information asymmetry. However, they are coming with their own challenges and drawbacks. Reputation systems can be vulnerable to manipulation of fake reviews (Mayzlin et al. Dover, & Chevalier, 2014), warranties might have complex and restrictive terms (Kirmani & Rao, 2000), and government regulation might impose incremental costs on businesses (Healy & Palepu, 2001) or on consumers or lower-income workers (Klee, 2022). The choice and effectiveness of any given solution depend heavily on the specific market context.

2.2 A General Framework of Pricing Theory

Before applying pricing concepts, it is essential to establish a general framework for pricing strategies. Pricing, in general, is not only about covering costs. It is a powerful strategic tool used to segment markets, signal the value of the product or service, and is essential to maximize profitability. This section reviews the foundational, behavioural, and dynamic approaches to pricing, thus providing its broader perspective.

2.2.1 Classical Foundational Pricing Models

Three foundational pricing strategies form the basis of most pricing discussions: cost-plus, competitor-based, and value-based pricing.

Cost-Plus Pricing. A foundational, straightforward strategy, cost-plus pricing, determines price by calculating total production costs and applying a standard percentage markup (Doyle, 2011). This method’s appeal lies in its simplicity, perceived fairness, and the comforting guarantee that every unit sold will be profitable. However, this focuses only on internal costs at the expense of external market monitoring, which might indicate its primary and most significant weaknesses, extensively argued in modern pricing literature.

The critical drawback of cost-plus pricing is that it anchors price only to the producer’s internal metrics, while completely ignoring external market dynamics. It fails to account for consumer demand, perceived value of product or service, or even consumers’ willingness to pay. This poses a significant risk of being misaligned with market conditions (Nagle & Holden, 2016). This might lead to prices being set too high for the value offers, deterring sales, or too low, thus failing to capture the full value created for the consumer. Furthermore, the model creates disincentives to operational efficiency, as higher production costs would be passed on to consumers through higher prices

(Horngren et al., 2012). In some cases, it might even trigger the so-called "pricing death spiral," in which higher prices lead to a decline in demand. These limitations are particularly relevant for digital goods and services, where near-zero marginal costs make cost-plus pricing fundamentally illogical.

Competitor-based pricing. Competitor-based pricing is a pricing strategy in which a firm's pricing decisions are benchmarked against competitors. This approach is common in markets with low product differentiation and high consumer price sensitivity. This might lead producers to price strategically, above or below the competitive benchmark, to achieve specific market share or positioning goals (Kotler & Keller, 2016). While this approach is tactically necessary in many industries, a single focus on competitors' pricing might carry a significant risk of starting destructive pricing wars. Such price wars might diminish profitability for all firms in the market, as they become trapped in a cycle of retaliatory price cuts. Therefore, firms might often shift their strategic direction from competitor-based pricing to focus more on other factors, such as branding, service, and quality, to create value beyond price alone (Rao et al., 2000). This might remain a dominant approach in digital markets, where consumers can easily compare prices. Therefore, engaging in price wars in digital markets might pose a greater risk. Recent research shows that algorithmic pricing, now common in e-commerce, can accelerate these conflicts and lead to new forms of "tacit collusion" in which competing AIs might learn to keep prices artificially high without any explicit agreement (Ezrachi & Stucke, 2020). In response, as Rao et al. (2000) have indicated, strategic emphasis might shift from competitor-based pricing; in the digital world, they might focus more on cultivating brand communities, managing online reputations, and delivering superior user experience (Grewal et al., 2021).

In oligopolistic markets, the principles of strategic interdependence, in which a firm's optimal choice depends on its rivals' anticipated actions, govern. The analysis of this interaction is a key topic in industrial organization economics, which uses non-cooperative game theory to model firm behaviour (Tirole, 1988). Contemporary research also uses these models to analyse how platform-based ecosystems, such as those managed by Apple and Amazon, operate as complex oligopolies in which competition occurs not only over price but also over control of data and the platform's architecture. In essence, the primary competition is shifting from pricing products to governing markets, where defining the rules of interaction becomes strategically more powerful than any price point (Jacobides & Lianos, 2021).

Value-based pricing. Value-based pricing, in general, is anchoring a product's price to the customer's perceived value rather than production costs or competitors' prices. This strategy is widely regarded as one of the theoretical ideals in marketing and strategy literature (Nagle et al., 2016). Its theoretical superiority stems from the direct alignment of price with the economic situation and the psychological benefits customers receive. This enables firms not only to capture a fair share of the value it creates, but also to foster stronger customer loyalty and better profitability (Anderson et al., 2006).

Even though this acknowledged superiority, a significant part of academic research points to a persistent "value-based pricing paradox", where the strategy's practical adoption remains far less than its strong theoretical foundations suggest (Töytäri et al., 2017). This gap between theory and practice often comes from significant implementation barriers. Firms are facing two key challenges: value quantification and value communication. Firstly, it is challenging to quantify the value, whereas costly market research is needed to assess the offering and its economic impact. Subsequently, it isn't easy to establish effective value communication to credibly convey differentiated value to the customer (Anderson et al., 2006). Internal hurdles often compound these external challenges, as Hinterhuber (2008) and, more recently, Liozu (2021) have identified the lack of cross-functional integration, salesforce resistance to defending higher prices, and the lack of a "pricing-oriented culture" driven by senior leadership.

2.2.2 Behavioural Economics and Psychological Pricing

Behavioural economics demonstrates that consumer decision-making often deviates from pure rationality and is influenced by social, psychological, and emotional factors. This perspective of bounded rationality acknowledges that cognitive and informational limits lead customers to rely on the mental shortcuts, or heuristics, which can result in systematic biases (Tversky & Kahneman, 1974). Key pricing tactics identified in the literature include charm pricing, price anchoring, framing, and loss aversion.

Charm pricing strategy, also known as odd-even pricing, involves setting prices just below a round number (i.e. €9.99 instead of €10.00). Its effect is attributed to the left-digit bias, a cognitive phenomenon in which consumers anchor the price on the leftmost digit, leading them to see €9.99 as significantly lower than €10.00 (Thomas & Morwitz, 2005).

Price anchoring strategy usually leverages the anchoring and adjustment heuristic, where individuals rely on an initial piece of information, so-called "anchor", when making further decisions (Tversky & Kahneman, 1974). In a pricing context, firms present a high-priced anchor first, which makes the following, lower-priced options appear more reasonable in comparison, thus guiding consumers towards the firm's preferred choice. Therefore, in the context of digital subscription services, a high-priced enterprise plan and low-priced Basic plans with limited functionality act as an effective anchor, which makes the middle-priced professional plan be seen as the best deal for the consumer (Keenan, 2025)

Framing and loss aversion. The way pricing is presented, known as framing, might significantly influence consumers' choices. The principle stems from prospect theory, which states that the psychological impact of a loss is much greater than that of an equivalent gain (Tversky & Kahneman, 1974). Therefore, framing a price in terms of the gain, for instance, a €50 discount, is usually much more persuasive than framing it as a cost (Levin et al., 1998).

2.2.3 Dynamic Pricing

Dynamic pricing, also known as surge or real-time pricing, is a pricing strategy in which prices fluctuate in response to changes in market dynamics, such as shifts in demand and supply or competitors' actions (Haws & Bearden, 2006). Even though this concept is not new, its sophistication and dominance have increased with the rise of e-commerce, which provides an infrastructure for real-time data collection and price adjustments based on it (Elmaghraby & Keskinocak, 2003). Its effective implementation relies critically on data analytics, with firms utilizing complex algorithms to process large datasets. These datasets usually cover everything, from historical sales and competitors' pricing to real-time consumer behaviour. This might even encompass exogenous factors, such as weather, to continuously estimate the optimal price to maximize revenue or profits (Agrawal et al., 2018; McAfee & Brynjolfsson, 2017).

The strategic adoption of dynamic pricing involves a complex trade-off: potentially high returns balanced with significant risk. In theory, the strategy might enhance profitability by allowing firms to capture consumer surplus, by aligning prices with the customer's willingness to pay (Shapiro & Varian, 1998). It also enables remarkable adaptability in response to market shocks and can serve as an efficient tool for managing different inventory sales, such as airline seats or hotel rooms (Gallego & van Ryzin, 1994). However, dynamic pricing may also have drawbacks. Research shows that frequent price changes can provoke strong adverse reactions, decreasing brand trust and long-term loyalty, as customers may perceive the practice as manipulative or unfair (Haws & Bearden, 2006).

Furthermore, when competing firms deploy these dynamic pricing algorithms, there is a risk of algorithmic collusion. In this scenario, these systems can learn to coordinate supracompetitive prices to maintain higher profitability. On the other hand, it might trigger aggressive price wars that might erode industry-wide profitability (Calvano et al., 2020).

2.2.4 Versioning and Bundling as Strategic Approaches

Versioning and bundling are powerful pricing strategies that are often categorized as second-degree price discrimination. These strategic approaches are well-suited to information goods due to their unique structure.

Versioning. Versioning, also known as quality discrimination, is a strategy in which a company creates different versions of a product, each with different quality or features, and sells them at various prices (Belleflamme, 2005). This approach encourages customers to self-select the option that best fits their budget and needs. As Shapiro and Varian (1998) argued, versioning is exceptionally effective for information goods. This is because offering lower- or higher-quality versions of the same good does not differ much in cost for the service provider (Belleflamme, 2005; Linde, 2009). For instance, developers can easily create a "basic" version by deactivating some of the features from the "professional" version (Keenan, 2025).

Bundling. Product bundling is a strategy where two or more distinct products are sold together as a package for one price, which is typically less than what a customer would pay for them individually (Stremersch & Tellis, 2002) This approach works exceptionally well for information goods because the marginal cost of adding another digital item to a package is virtually zero (Bakos & Brynjolfsson, 1999; Linde, 2009).

The economic logic behind bundling is its ability to reduce the wide variation in how different consumers value products. Bakos and Brynjolfsson (1999) famously argued that while a customer's willingness-to-pay might be unpredictable for any single item, the law of large numbers dictates that their willingness-to-pay for a large bundle of items becomes much more predictable, clustering tightly around an average value. This predictability allows a seller to set a single bundle price that captures more consumer surplus than if the items were sold separately.

2.2.5 Theoretical Synthesis

Building on classic models, recent research has started to analyse more complex pricing scenarios, such as how to bundle products with multi-unit demand (like services with usage fees) or how to price bundles in subscription markets (Wu et al., 2024).

The shift from simple pricing models like cost-plus to complex, data-heavy strategies like value-based and dynamic pricing is not just a theoretical exercise; it was driven by the technological revolution that made it cheap to collect, store, and analyse massive amounts of data. Older models were relatively informationally cheap, needing only internal cost figures (cost-plus pricing) or competitor prices (competitor-based pricing). Modern strategies, in contrast, are quite informationally expensive. Value-based pricing demands deep research into customer psychology and their willingness-to-pay (Anderson et al., 2006), while dynamic pricing needs a constant flood of real-time data to function (Haws & Bearden, 2006)

This parallel evolution of pricing strategy and data technology has created an entirely new kind of information asymmetry. Foundational economic theories focused on an imbalance where the seller knew more about the *product's quality* than the buyer, like in Akerlof's (1970) paper about the "lemon". Today's pricing strategies are built on an information imbalance in which the firm, using its vast data-collection tools, knows more about the *customer's* behaviours, preferences, and price sensitivity than the customer does about the company's algorithm or data usage. It might even capture exogenous factors, thus influencing consumers' demand for products (McAfee & Brynjolfsson, 2012; Elmaghraby & Keskinocak, 2003; Haws & Bearden, 2006). This fundamental pivot from "product information asymmetry" to "customer information asymmetry" is the key to understanding the modern economics of the mobile app market, where user data itself has become a central currency.

2.3 Narrowing the Focus – Pricing and Information Asymmetry in the Mobile App Sector

Mobile applications are a prime example of digital information goods, and their unique economic characteristics demand a fundamental rethinking of traditional pricing strategies. Therefore, when analysing the mobile app markets, it is also necessary to understand the economy of digital goods (Quah, 2003; Belleflamme, 2016).

2.3.1 Near-Zero Marginal Cost and Non-Rivalry

While developing the "first copy" of an app or any other digital good incurs substantial sunk costs, the marginal cost of reproducing and distributing it to a new user is effectively zero (Belleflamme, 2016; Quah, 2003). This cost structure alone makes traditional cost-plus pricing models almost entirely irrelevant. The economic challenge is also evident in the fact that apps are non-rival, meaning that one person's use of an app or any other digital good doesn't reduce its availability or value to others (Quah, 2003). This combination resembles a classic public good problem. The socially efficient price would equal the marginal cost (zero), but pricing at zero would yield no revenue to cover the high initial development costs (Quah, 2003). Navigating through this fundamental tension is the central strategic challenge in the app market.

2.3.2 Mobile Applications and Monetization Strategies

The most popular monetization models are prevalent in the mobile application market and cannot be seen solely as business decisions but also as strategic responses to navigate information asymmetry. Tissier (2023) and Arguelles (2025) identify a few key mobile app monetization strategies that are among the most applicable in mobile app markets. These include:

Paid (Pay to Download). The paid apps model is one of the most traditional models, in which users pay an upfront, one-time fee to download and use an application (Arguelles, 2025). The price point for downloading the app can serve as an effective signal of quality. A developer charging a premium for the application might signal that it provides sufficient value to justify the cost. It is applicable to apps that offer unique products or have established market presence (Arguelles, 2025). In a market with plenty of free alternatives, charging a price is a risky strategic move for a lesser-known brand or app, as it can deter some potential customers. Additionally, lesser-known and new entrants to the app market could be exposed to signal jamming, where the value, which they charge their consumers, would be falsified by the poor reviews (Mayzlin et al. Dover, & Chevalier, 2014; Dellarocas, 2003)

Free App pricing model. The Free App pricing model is set to maximize the number of downloads without putting any paywalls or barriers that may prevent users from using it. Some of the applications are keeping their approach to stay **Truly Free**. However, they might approach monetization in different ways, such as providing services, such as advertising space (Tissier, 2023). In an **ad-supported** model, developers create a two-sided market, acting as intermediaries between users and ad providers. These types of markets often include pricing structures that subsidize one side to attract a critical mass of users, while making the platform more valuable for the other (Evans & Schmalensee, 2007; Rochet & Tirole, 2006). The attention of users and their data is the product that is being sold to advertisers. Therefore, this model might introduce a significant information asymmetry related to data privacy and security. Users are often not well informed about the type and extent to which their personal data is collected (Smith, 2019). Also, an information gap exists on how the data is handled, how it is used to create detailed user profiles, and with which external parties the data is shared. This privacy price could be seen as a potential hidden cost that is not transparent at the point of download (Grace et al., 2012).

Freemium app pricing. The Freemium app pricing model is among the most popular models in the app economy. It involves offering a basic or limited app version for free, with the option for users to purchase an upgrade to the so-called “premium” version with more advanced features (Walker, 2024). The freemium model is a powerful solution to information asymmetry and acts as a sampling or trial mechanism, as users can experience the core functionalities of the app’s quality before upgrading to the premium version. Research suggests that this sampling effect can increase the potential demand for the premium version, especially when the initial perception of quality is moderate or when the premium version offers a significant upgrade versus the free version. (Deng et al., 2023). By demonstrating the value in the base and free version of the application, developers are building trust, which creates a positive spillover effect, which might incentivize the users to purchase and convert to unlock the full and premium version of the application, essentially overcoming the initial information gap.

Freemium applications often use the IAP model, which allows users to purchase content, features, virtual currencies, or other items within the app (Arguelles, 2025). The model enables second-degree price discrimination, allowing developers to extract different values from users based on their needs and willingness to pay. Even though this might enable developers to uncover additional revenue opportunities, this model might create a new form of information asymmetry. For instance, in the gaming applications, information asymmetry might be intensified by its strategic design. For example, a user may download a free game only to find out later that meaningful progress is available only with continuous spending, which is unknown before downloading (Ruston, 2025). Also, the interfaces of the applications might employ dark and unknown patterns to create an artificial scarcity of some items, which would nudge customers to make in-app purchases or engage in microtransactions with incomplete or misleading information (Zagal et al., 2013). This is a result of developers having superior knowledge of the app's lifecycle and the game's internal economy, which allows them to extract value from consumers who are not fully informed.

The Freemium model is often combined with the subscription model, in which users pay a recurring fee (e.g., annual, monthly, or weekly) for continuous access to an app, its content, or features (Arguelles, 2025). From an information asymmetry perspective, the subscription pricing model has an inverse relationship with moral hazard. For instance, when the application is limited to a one-time purchase (as in the freemium category), developers have weaker incentives to update or introduce new features regularly. Also, the subscription model offers a powerful incentive to maintain the application, provide ongoing support, and introduce new features after a sale is complete. One key reason is to incentivize users to keep using the application and increase customer retention. This aligns with the long-term interest of developers to keep their recurring revenue stream from the users, and for users also to keep using the application even post-first purchase (Vagle, 2020).

The developers often combine the Freemium Model together with Ad-Supported, forming a **Hybrid** monetization model that incorporates both IAP and advertising. Unlike models that offer a single revenue stream, this approach helps address user heterogeneity by providing a time-money trade-off (Enache et al., 2025). This approach allows developers to monetize users with a high willingness-to-pay, while price-sensitive users are monetized by selling their attention to third-party advertisers (Wang, 2025). Essentially, this model should serve as a screening mechanism (Stiglitz & Weiss, 1981), which is caused by information asymmetry regarding not knowing the real user's valuation.

2.4 Information Asymmetry and App Pricing

The relationship between information asymmetry and pricing strategies in the app market might work both ways, even though developers, by employing one of the pricing models, might signal the quality of their applications. However, each different pricing model might employ other kinds of information asymmetry. Also, market uncertainty might influence which models are most viable and widely adopted, depending on the app's category and type.

2.4.1 Developer's Quality Signals

In the market's uncertainty, beyond employing different pricing strategies, the ecosystem of signals has also emerged to help users make informed choices. The literature identifies several key signals that developers and app stores are using to signal the quality of an application:

User Ratings and Reviews. User Ratings and reviews are perhaps one of the most prominent signals in the mobile app ecosystem. A high average star rating and a large number of positive reviews might serve as a credible signal of an application's quality and are among the most critical factors in app store ranking algorithms (Danilchik, 2025). It might also indicate the app's popularity and the demand for an application, which conveys the credibility and quality of the app (Deng et al., 2023).

Download Counts and Ranking. A high number of downloads and top positions in the app store charts serve as a strong signal for an application's relevance and popularity. Also, the application's number of downloads and ranking in app stores might signal the quality of the application to users, thus reducing, in a sense, users' uncertainty (Danilchik, 2025).

App Store Featuring. Being selected and featured by Apple or Google is considered a powerful endorsement. App stores are showcasing high-quality applications and business models based on factors such as user experience, UI design, innovation, uniqueness, and more. This acts as a strong signal that encourages users to download and potentially make a purchase in the application. It also enhances the developer's reputation (Danilchik, 2025).

Developer Reputation. In the online market, which is prone to adverse selection (i.e., users cannot distinguish a low-quality application from a high-quality one) and moral hazard (i.e., developers might misuse the user data, offer poor support, and updates), a developer's reputation might serve as a credible signal to show trust. As developers invest significant resources in creating and marketing the app, they have a strong economic incentive to maintain quality. Therefore, as Tadelis (2016) argues, reputation in online markets is a valuable capital asset that is costly to build and easy to destroy.

Update Frequency. Frequent app updates indicate the ongoing support for the application and its responsiveness to user feedback. Therefore, it may serve as a credible signal on the application for the users, thus reducing potential information asymmetry. Consequently, it helps improve the app store rankings mentioned above (Danilchik, 2025; Kanal, 2024).

Signal Jamming. However, even though the mentioned signals are pretty easy to observe and decide based on the information, this makes them relatively easy to manipulate, which might lead to potential signal jamming, where actors might skew the signals and mislead the users (Mayzlin et al., Dover, & Chevalier, 2014). The market for fake reviews and ratings is a documented phenomenon in which developers can purchase positive reviews to artificially improve their rankings and application visibility. Platforms like Google and Apple are actively combating fraudulent reviews by removing millions of them each year. However, the problem persists. Similarly, download numbers can be manipulated through bots or any other incentivized download campaigns. These examples might reduce the users' trust in the entire signalling environment, thus creating a crisis of credibility (Apple, 2025). Therefore, according to Spence (1973), when signals can be easily faked, they are essentially losing their value.

2.4.2 Pricing as a Signal and Response to Uncertainty

Given that the Developer's quality signals, such as users' ratings and download counts, can be easily jammed or manipulated, pricing is a credible, non-jammable signal for potential users. Therefore, the monetization model for the developers might not only be a financial decision, but also a strategic communication to the market.

Pricing as a Signal. As discussed, various pricing models might signal the developer's willingness to communicate their app to the market and address potential information asymmetry. For instance, the freemium model signals developers' confidence that the base version of the app's quality is high enough to drive conversions and successfully monetize (Deng et al., 2023). On the other hand, a high price might position the application as a luxury or a high-value niche product, thereby appealing to the heuristic that price is equal to quality (Kirmani & Rao, 2000). Roma & Ragaglia (2016) also identify that an upfront cost for an application might signal a high quality for an application, differently from free alternatives.

Uncertainty over the choice of Pricing. The level of the information asymmetry might influence which pricing strategies are most effective for the developer to maximise their revenue. As the empirical work by Deng et al. (2023) provides evidence that the positive effect of a free app version on the demand for the paid version is most applicable for apps with a moderate star rating. For instance, for low-rated applications, the expected benefits will appear too low given the cost of sampling. Similarly, for a high-rated application, the perceived application's quality is already guaranteed to be above the high threshold, and sampling provides little additional information. These findings suggest that the freemium pricing model may be most strategically valuable in contexts of moderate uncertainty.

2.4.3 Mobile Applications as Experience Goods

To understand the structural constraints new market entrants face, it is necessary to examine the mobile application market through the lens of information asymmetry (Akerlof, 1970) and experience goods theory (Nelson, 1970). From the developers' point of view, the decision-making process is not only about revenue maximization, but also becomes a strategic decision to reduce customers' ex-ante uncertainty. Ghose and Han (2014) have provided a theoretical basis for this friction, characterizing mobile applications as a classical experience good, in which users identify the true quality of an application only after downloading and engaging with it.

Ghose and Han's (2014) structural estimation of demand suggests an inverse relationship: as consumers gain usage information, their price sensitivity diminishes. Essentially, the uncertainty inherent in a new product acts more like a tax, discounting on a consumer's willingness to pay. Therefore, it means that a developer lacking initial reputation signals must lower their barrier to entry. However, Roma and Ragaglia (2016) argue that adopting a paid revenue model might signal high quality; the efficacy of this mechanism relies on the credibility of the signal.

Synthesizing these two perspectives reveals a specific trap for new entrants. If a developer charges an upfront fee, they prevent users from trying out and learning to use the application (Ghose & Han, 2014). At the same time, without an established reputation, they cannot rely on the signal that a high price indicates high quality, as suggested by Roma and Ragaglia (2016). Therefore, in this scenario, the developer is not selecting a revenue model but is instead forced into a Hybrid or Freemium approach to reduce the initial information asymmetry.

3. RESEARCH METHODOLOGY

A vast literature review has been synthesized on what is known about the topic. However, it is essential to understand how it is known. Some of the research reviewed in the mobile app economy is complex and presents significant data-related challenges. Therefore, potential difficulties should be considered before proceeding with further research.

3.1 Reviewing the Research Methodologies

The academic literature has employed various research methodologies to examine the relationships among information asymmetry, pricing, and performance in the mobile app market.

3.1.1 Econometric Analysis of App Store Data

This is among the most prevalent research approaches. In the Mobile App market, researchers often scrape data to build large-scale, cross-sectional, or panel datasets from the public-facing pages of app stores, such as Google Play and Apple's App Store. Then they use econometric techniques, such as app price, in-app pricing, average rating, number of ratings, reviews, and app category (Deng et al., 2023). The key benefit of this approach is that it enables the analysis of a large number of apps and the use of real-world data. It can also establish and show potential correlation between the variables. However, as correlation does not imply causation, this model might fail to establish causality due to endogeneity and omitted variable bias. One good example in the mobile app market is whether good ratings lead to more downloads, or whether growth in downloads leads to more ratings. Logically, there should be an existing correlation between these two variables, but an unanswered question remains: which factor causes which one.

3.1.2 Event Studies

This is a specific type of econometric analysis that analyzes the impact of a particular event on the outcome variable. For example, Deng et al. (2023) analysed changes in download ratings for a paid app immediately before and after the developer introduced a free "lite" version. This approach might provide a stronger causal relationship than standard cross-sectional regression. However, it is limited to studying single phenomena that occur as distinct, observable events.

3.1.3 User Surveys and Questionnaires

To understand users and the psychological drivers of user behaviour, researchers often conduct user surveys and questionnaires. This method involves directly asking users about their perceptions of quality, their trust in reviews, privacy concerns, and their willingness to pay for different features or under different pricing models (Momenzadeh & Camp, 2017).

3.1.4 Controlled Experiments

One of the best ways for researchers to establish clear causal relationships is to conduct experiments. In a lab experiment, participants might be presented with simulated app store pages where elements like price and user rating are varied to see the user's download intentions. In a field experiment, a developer might partner with researchers to run an A/B test on app features with live users to assess the statistical significance and impact of the changes (Momenzadeh & Camp, 2017). However, due to the lack of available resources, such as a developed mobile application with a significant user base, this approach for the research will not be considered.

3.2 Navigating with the Data

The challenge of data access shapes research in the mobile apps market. The mobile app market is notoriously opaque, forcing researchers to tackle the data limitations.

3.2.1 Data Sources

The data to be used in app research might be extracted from a few primary sources:

Public App Store data. Scraping is one of the most common sources. It includes data visible on the app store's page, such as price, title, description, developer's name, average rating, number of ratings, update history, and user reviews. While it looks like rich data, most often it might be incomplete, and app stores might also change their layouts or the data they are presenting (Deng et al., 2023)

Data from Analytics Firms. Based on research of the research, conducted personally, companies like Sensor Tower and AppTweak provide access to more detailed data, including estimates of downloads and in-app purchase revenues. Even though the data might be a valuable supplement to previously publicly scraped data, most of these platforms are subscription-based, so that that access can be expensive. Also, the accuracy is difficult to cross-check, and the method used to generate the estimates (i.e., revenue) might be unclear. This approach did not provide successful results due to the limited financial resources to acquire the costly subscription to access the analytics firms' data.

3.2.2 Documented challenges and limitations

The literature reviewed indicates several critical limitations that might impact the previously mentioned datasets.

Survivorship Bias. App stores have quite a dynamic environment, where unsuccessful apps are often removed by the developers or the platform itself. Therefore, any dataset scraped from today's app stores will naturally be skewed towards the apps that have survived and are likely to be successful. This survivorship bias can easily lead to overestimating an average application's quality and lifespan (Maj & Pavel, 2025).

Limited visibility into essential financial and behavioural metrics. A key challenge in research is that the most critical variables for deep economic analysis are often hidden or inaccessible. The basic data points, like developer costs, actual revenue, and proper user engagement measures, are treated as proprietary information (Momenzadeh & Camp, 2017; Roma & Regaglia, 2016)

Data Accessibility and Platform Gatekeeping. The role of platforms like Apple and Google as powerful data gatekeepers creates significant research hurdles. These companies have been criticized not only for providing incomplete or inaccurate data but also for making it exceedingly difficult for independent researchers to gain access. This practice often continues even when they are legally mandated to share data for vital research, such as studying the spread of misinformation (Maj & Pavel, 2025).

3.2.3 Methodological Responses: The Use of Proxies

Given the data limitations regarding the free and easy access to the data sources, a central feature of empirical research in mobile applications is the use of proxies. A proxy is an observable, measurable variable that stands in for a theoretically essential but unobservable construct (Snow et al., 2005). The studies analysed often rest on the strength and justification of specific proxies. Common proxies from the reviewed literature include:

Proxy for App Quality: Researchers typically gauge an app's quality by its average star rating and the total number of ratings (Deng et al., 2023; Roma & Regaglia, 2016). In addition, being featured in the app store is often considered another strong signal of high quality (Danilchik, 2025).

Proxy for App Demand/Popularity: Because actual download numbers are private, researchers often estimate an app's popularity or user base size by looking at the total number of ratings or its official store rank (Deng et al., 2023)

Proxy for Developer Effort/Commitment: The frequency of app updates is frequently used as a proxy for ongoing developer effort and investment in the app (Kanal, 2024)

3.3 Data Description and Sample Selection

The empirical analysis relies on a cross-sectional dataset constructed from two dominant mobile app ecosystems: the Google Play Store (Android) and the Apple App Store (iOS). To build this dataset, publicly available application metadata were systematically scraped using automated web crawling algorithms. This approach was chosen to ensure that the data would be unbiased and representative of the market, capturing a broad spectrum of applications, from niche tools to the most popular ones.

The data was collected in late 2025 to ensure that the data is collected based on the most recent data, and potential survivorship bias would not affect the extracted results. The final analytical sample consists of two data sets: 47096 Android observations and 94900 iOS observations. A dual-platform approach was selected to mitigate potential market-specific bias and to capture distinct market structures, as described by Ghose and Han (2014). Applications with incomplete data (i.e., null ratings or missing descriptions) were removed to ensure the validity of information asymmetry proxies. Also, each marketplace provides slightly different publicly available data, so they were separated into two datasets. The resulting datasets provide a robust, granular foundation for analyzing developer signaling behavior across categories such as Utilities, Games, Productivity, Education, etc.

3.4 Research Design and Model Selection for the Research Question 1

To analyze the first research question: How do varying degrees of information asymmetry between mobile application developers and consumers impact the selection of different pricing models within the mobile application marketplace? – This study would employ a Multinomial Logit Regression (MNL) model. The choice is primarily driven by the fact that the dependent variable is categorical and unordered, reflecting the developer's discrete decision regarding monetization strategies.

The dependent variable for this analysis is the developer's choice of monetization strategy, which is a nominal, unordered categorical outcome ($Y \in$ {Free, Paid, Freemium, Truly Free}).

While prior studies, such as Roma and Ragaglia (2016), used fixed-effects linear regression to assess the performance of these strategies, our research objective differs: we aim to predict how ex-ante signals affect the selection of the pricing strategy itself. The econometric literature establishes the Multinomial Logit model as the standard approach for analyzing discrete choices in which the alternatives are mutually exclusive and exhaustive (Greene, 2012). This approach allows us to estimate the probability of an app developer selecting a specific pricing model, relative to a baseline, which is conditioned on the information asymmetry variables and other control variables.

3.4.1 Operationalization of Variables

The variables are constructed from two different datasets: Google Play (Android) and Apple App Store (iOS). Although the platforms are different and have their own market specifics and publicly available data, variables were harmonized to ensure that the results and determining factors are comparable.

A) Dependent Variable: Pricing Strategy (*Y*)

The dependent variable, monetization strategy, is categorized into five distinct types, based on the presence of upfront price, in-app purchases (IAP), and advertising. The distinction and categorization, based on the data, are presented in Table 1 below.

Table 1

Categorization of the Dependent Variable

Category	Definition	Logic
Hybrid (Reference)	Price = 0, Has both Ads & IAP	Diversified strategy: maximizes revenue by segmenting users into payers (via IAP) and “non-payers” (via Ads)
Truly Free	Price = 0, No Ads, No IAP	The lowest barrier to entry, essentially no monetization
Paid	Price > 0	High barrier, which requires strong quality signals to justify upfront cost
Freemium (IAP Only)	Price = 0, Has IAP only, No Ads	Monetization through In App Purchases
Ad-supported	Price = 0, Has Ads only, No IAP	Monetization of attention, rather than direct upfront payment;

Source: Prepared by the author, based on literature reviewed

As a baseline, the Hybrid pricing model will be selected due to its market dominance, as shown in Table 2. This approach would allow for the interpretation of other pricing strategies as deviations from the current standard practice in the market.

Table 2
Distribution of App Monetization Strategies Across Android and iOS Platforms

Pricing Strategy	Android	iOS
Hybrid	20,673	72,665
Truly Free	9,238	4,122
Ad Supported	5,311	2,305
Freemium	9,883	12,391
Paid	1,991	3,417
TOTAL	***47,096***	***94,900***

Source: Prepared by the author, using the publicly available data, scraped from Google Play Store (Android) and Apple App Store (iOS)

B) Independent Variables: Information Asymmetry Signals

Following the signaling theory framework (Spence, 1973), potential variables are selected as observable proxies for the unobservable quality.

Information Disclosure (Log(Description Length))

• *Operationalization*: Natural log of character count of the app description

• *Theoretical basis*: Longer descriptions reduce search costs and information asymmetry by providing more details about the features and utility of the application. It is possible to hypothesize that Paid apps require longer descriptions to justify their upfront cost compared to free-to-download apps

Social Proof (Rating, log(Review Count)

• *Operationalization:* Current average star rating and natural log of the total review count

• *Theoretical basis:* Higher average ratings and larger volumes of ratings can act as a reputation mechanism that indicates an app's quality and popularity (Deng et al., 2023). A high number of ratings might signal an app's market maturity, allowing developers to switch from ad-supported to Freemium or Paid models.

Developer's legitimacy (has_website, Name Length (Chars))

• *Operationalization:* Binary dummy for website presence, character count of App name

• *Theoretical Basis:* A dedicated website is already a costly signal of long-term commitment. Key costs are coming from creating the website, its support, development, and maintenance. Therefore, the existence of a developer's website shows a long-term commitment to an app. On the other hand, based on a preliminary inspection of the data, long app names stuffed with various keywords might be associated with low-quality or "spam" apps.

Developer's commitment (Log(Days Since Update)):

• *Operationalization:* Natural log of days since the last update

• *Theoretical basis:* As Kanal (2024) notes, developers' commitment can be measured by the frequency of updates. Since the frequency could not be retrieved, the next best alternative could be to measure the days since the last update of the application. If an application is **updated regularly, it** shows the **developer**'s **commitment to maintaining the app and ensuring** quality.

C) Control Variables

In order to isolate the effect of information asymmetry from market-specific and app-specific factors, the following control variables are included:

Geographic Market Fixed Effects (Country Dummies): Market conditions, such as purchasing power parity and cultural attitudes towards digital goods. According to various market reports, the United States dominates in IAP revenue, with the United Kingdom, Germany, and France among the top 10 countries (Sensor Tower, 2025). The dummy variables are introduced for the country data collection to control for macroeconomic heterogeneities:

- United States (US): Treated as Baseline Reference Group
- Germany (DE): Dummy variable (=1, if store is Germany)
- France (France): Dummy variable (=1, if store is France)
- United Kingdom (GB): Dummy variable (=1, if store is in the United Kingdom)

Complexity of the Application (Log(Size in MB)): This control variable is applicable for the iOS model only, as it was available for the iOS app store

A larger size of the application usually implies the developer's investment into the quality and various assets within the app (i.e., graphics, visuals). A low-quality developer, who is creating the low-quality app (lemon), is less likely to invest in the resources needed to produce a good application. Thus, the app's size controls the quality of the application. This control variable is applicable for the iOS model only, as it was available in the iOS App Store.

Age of the application (Log(App Age)): This variable controls for the application's lifecycle stage. It calculates the days since the app's release to this day. Older applications are more likely to have adopted a paid model, as in the market, freemium applications or a hybrid approach were adopted relatively recently. Therefore, the older the application, the more likely it has adopted a paid model

Popularity of Application: This variable controls for the number of downloads for each application and is available for Android models only. However, the data available in the Google Play store does not show the exact number of downloads; it is indicated as an ordinal value (i.e., 5000+, 10 000+, 20 000+, etc.), thus it will be treated as a dummy variable with the smallest bin as a reference.

Category: This variable controls for category-specific monetization standards and other market specifics, which are different for gaming apps, utility apps, etc. The variable is set to be treated as a dummy for each app category.

3.4.2 Econometric Specification

Multinomial Logit Regression (MNL) is chosen to estimate and assess the research question. The probability that the application i in the country c selects the pricing strategy j relative to the baseline ($j = 0$, Hybrid) is estimated using Model 1.

Model 1:

$$\ln\left(\frac{P(Y_{ic} = j)}{P(Y_{ic} = 0)}\right) = \alpha_j + \beta_{j1}\boldsymbol{Signals}_i + \beta_{j2}\boldsymbol{Controls}_i + \delta_j\boldsymbol{Country}_c + \varepsilon_{ic} \qquad (1)$$

Where:

- $j \in \{\text{Paid}, \text{Freemium}, \text{Ad} - \text{only}, \text{Hybrid}\}$
- $Signals_i$: This variable in the equation is defined as a vector of Information Asymmetry proxies (Independent Variables), such as description length, social proof, developer's legitimacy, and developers' commitment
- $Controls_i$: This variable in the equation is defined as a vector of all control variables.
- $Country_c$: Vector of geographic dummy variables (DE, FR, GB), where the US is treated as a baseline and is captured in the intercept (α_j)
- δ_j: This coefficient represents the likelihood of choosing a pricing strategy j in a specific country relative to the US

3.4.3 Hypothesis for Research Question 1

Based on the established theoretical framework, the following hypotheses are to be tested to address the first Research Question:

- H_{1a}: Higher degrees of information asymmetry (indicated by shorter descriptions, lack of website, low ratings, and volume) are more likely to be positively associated with Ad-supported and Truly Free models, as developers are lowering the entry barriers and trying to mitigate the consumer risk

- H_{1b}: Strong signalling capabilities (high ratings, recent updates, longer descriptions) will be positively associated with Paid and Freemium models, as these signals effectively reduce the information gap, allowing developers to capture more value

3.5 Research Design and Model Selection for Research Question 2

To address the second research question: *To what extent can the implementation of specific monetization strategies mitigate market uncertainty and enhance revenue stability for mobile application developers?* – This study utilizes the Ordinary Least Squares (OLS) regression framework with some log-transformed performance variables

In the mobile app ecosystem, developers may use a freemium pricing model to signal developers' confidence in the app's quality, that it would drive conversions, and that it would successfully monetize (Deng et al., 2023; Roma & Regaglia, 2016). This strategy might effectively mitigate users' uncertainty in the app's quality. However, since revenue data is not available in public sources, the literature suggests that the volume of user ratings is a reliable proxy for an app's market success and revenue stability (Deng et al.,2023). The bigger the volume of ratings, the more popular and more stable the app is in terms of revenue.

After the initial review of data, the distribution of ratings across app stores appears to follow a traditional power law, with a small percentage of apps accounting for the vast majority of engagement. Because of this reason, the dependent variable (rating_count) is log-transformed. This would ensure that residuals are normally distributed and would allow interpretation of coefficients as percentage changes, providing a more detailed view to see how switching monetization strategies would impact the app's stability in the market.

3.5.1 Operationalization of Variables

Similarly to Research Question 1, variables were harmonized with some differences, depending on the platform of the Model (iOS or Android)

A) Dependent Variable: Market Penetration and Stability

- *Operationalization*: Apps success proxy (ln_rating_count): The natural logarithm of the total number of ratings
- *Rationale*: Number of Ratings is a continuous metric that captures active user validation. A higher volume of ratings indicates that the developer has successfully navigated uncertainty in the market and reached stable user acquisition

B) **Independent Variables: Monetization Strategies**

To analyse the comparative efficacy of different models, we employ the four monetization dummy variables that were constructed for the first econometric model, having the Hybrid pricing model as the baseline ($j = 0$):

- Paid Dummy: 1 if app has an upfront cost, 0 otherwise
- Freemium Dummy: 1 if the app is free, but contains In-App purchases only
- Ad-Supported Dummy: 1 if the app is free, but contains only ads in the application
- Truly Free Dummy: 1 if the app does not have both in-app purchases and ads

As shown in Table 2, the Hybrid strategy is a market-dominant pricing model. Therefore, it allows us to examine other pricing strategies as deviations from standard market practice.

C) **Control Variables**

To isolate the possible effects of the monetization strategy from other success drivers, the following control variables are included in the model:

Quality signal (Rating): Average star rating. High-quality and higher-rated apps attract more users; therefore, it is necessary to control for this to see the pure effect of the pricing model.

Information Disclosure (Description_length): Longer descriptions reduce search costs and uncertainty by providing more details about the features and utility of the application

Developer's legitimacy (name_length): Controls for the impact of app naming on discoverability. However, based on a preliminary inspection of the data, long app names stuffed with various keywords might be associated with low-quality or "spam" apps.

App Complexity (size_mb): This control is applicable for iOS only. It controls for the developer's commitment to various in-app elements, such as visual assets, screens, looks, and functionalities.

Popularity of Application: This variable controls for the number of downloads per application and is available only for Android models. However, the data available in the Google Play Store do not show the exact number of downloads; they are reported as ordinal values (i.e., 5000+, 10 000+, 20 000+, etc.). Thus, it will be treated as a dummy variable with the smallest bin as the reference.

Age of the application (Release_date): This variable controls for the possible effects of the app's age. As indicated in RQ1, older apps are more likely to have adopted a paid pricing model. Also, the older the application, the more likely it is to have an advantage in rating volume.

Geographic Fixed effects: dummies for DE, FR, and GB, with the US as the baseline. This control variable is used to account for regional variation in apps' adoption rates.

Category Fixed Effects: Dummies for categories (i.e., Games, Utilities) which are employed to control for different market behaviour across the various genres of the application.

3.5.2 Econometric Specification

To analyze the impact of monetization strategies on market success and the mitigation of uncertainty, this research employs Ordinary Least Squares (OLS) Regression with clustered standard errors. The market penetration for an application i in the country c and category k is estimated using Model 2.

Model 2:

$$\ln(RatingCount_{ick}) = \alpha + \sum_{j=1}^{4} \beta_j \boldsymbol{Strategy}_{ij} + \gamma \boldsymbol{Controls}_i + \sum_{c=1}^{3} \delta_c \boldsymbol{Country}_c + \sum_{k=1}^{K} \theta_k \boldsymbol{Category}_k + \varepsilon_{ick} \tag{2}$$

Where:

- $j \in \{\text{Paid, Freemium, Ad} - \text{only, Truly Free}\}$: The specific monetization strategy employed by the developer, where Hybrid is treated as a baseline
- $Controls_i$: This variable in the equation is defined as a vector of Control variables, such as Quality signal, Information Disclosure, Name length, and others
- $Country\ _c$: This variable in the equation is defined as a vector of geographic dummy variables (DE, FR, GB) with the US treated as a baseline
- $Category\ _c$: This variable in the equation is defined as a vector of binary dummy variables, where each represents a specific application category

3.5.3 Hypothesis for Research Question 2

As mobile applications are experience goods, where the quality of the application is essentially unknown to consumers before purchase (Ghose & Han, 2014; Nelson, 1970), different monetization strategies that do not require upfront costs allow users to perform a risk-free quality verification. The paid model essentially imposes a financial barrier that increases market uncertainty (Ghose & Han, 2014). Therefore, we argue that free-to-download strategies would reduce market friction and lead to higher adoption rates, compared to Paid Models. Thus, the following hypothesis with the model will be tested:

- H_2: Mobile applications that utilize free-to-download monetization strategies (Freemium, Ad-supported, and Truly Free) will have significantly higher rating counts compared to Paid applications.

4. EMPIRICAL ANALYSIS: QUANTIFYING THE IMPACT OF INFORMATION ASYMMETRY ON PRICING STRATEGY SELECTION AND MARKET STABILITY

4.1 iOS Marketplace: Model Specification and Fit for Research Question 1

To investigate Research Question 1 (RQ1), the Multinomial Logit Regression (MNL) Model 1 was estimated using data from the iOS App Store. The dependent variable was pricing strategy choice, where Hybrid pricing Strategy (Free application, that has In-App Purchases and supports ads), due to its market dominance, allowed for the interpretation of other pricing strategies as deviations from the current standard practice in the market.

As seen in Annex 2, Table 8, the model shows strong goodness-of-fit, with McFadden's Pseudo R-squared at 0.216. In the context of discrete choice modelling, a McFadden's R-squared in the 0.2-0.4 range is widely considered as an excellent fit, representing a quite high level of explanatory power, comparable to R-squared in linear regression (Domencich & McFadden, 1975). Therefore, the selected vectors of information asymmetry signals and control variables effectively capture drivers of monetization strategies in the iOS ecosystem.

4.2 Hypothesis Testing and Variable Analysis for iOS Ecosystem

To test the research hypothesis and answer the Research Question, Coefficients were analyzed using Multinomial Logit Regression (MNL). As established in methodology section, Hybrid Model ($j = 0$, Hybrid) served as a reference category. This is strategically important, as hybrid apps (combining In-App Purchases and Advertising) represent one of the most complex monetization strategies, and they dominate the market, as per the collected sample. Therefore, the results, which are presented in Annex 1, reveal how variations in information asymmetry force the developers to deviate from the dominant strategy towards the simpler models, like Truly Free or Paid.

4.2.1 Testing H_{1a}: Reducing Barriers in High-Asymmetry Contexts

Hypothesis H_{1a} states that a higher degree of information asymmetry, shown by shorter descriptions, lack of web presence, lower ratings, and its volume, is positively associated with Ad-supported and Truly Free models. This economic rationale is coming from the fact that, as developers cannot effectively signal quality, they must lower the barriers to entry to zero to mitigate the consumers' perceived risk.

Initial empirical results for the iOS market provide robust support for H_{1a}, specifically through mechanisms of "Search Costs" and "Costly Signalling."

A) Description Length: The "Information Gap" Proxy

The Variable Log(Description Length) serves as a direct proxy for the amount of information provided to the consumer before the purchase.

The empirical research indicates strong negative coefficients for both Truly Free ($\beta = -0.711, p < 0.001$) and Ad-supported ($\beta = -0.687, p < 0.001$) strategies relative to the Hybrid baseline. Considering the Odds Ratio measure, for every one unit increase in the natural log of description length, the odds of an app being Truly Free or Ad-Supporter (relative to Hybrid) are cut roughly in half. These findings imply that developers of truly free or ad-supported apps provide significantly less textual information compared to the Hybrid Apps. Economically, this suggests that these developers are substituting the information with accessibility. Due to the reason that the application is free to download, the consumer's cost of testing is merely matching its time to download an application. Thus, there is no significant pressure on the developers to reduce search costs using the lengthy descriptions. The "free" price tag is already acting as a mechanism to absorb the risk of information asymmetry: If an application turns out to be a "lemon", then it means that the user did not lose any money, just his time to download and test it.

B) Website presence: Costly Signal

The dummy variable Has_Website tests the costly signaling theory (Spence, 1973). Maintaining a dedicated website requires capital and effort, signaling long-term commitment to an application.

The empirical research suggests that the Truly Free strategy in the iOS ecosystem is negatively associated with having a website ($\beta = -0.336, p < 0.001$). Also, apps with a website are roughly 28% less likely to be Truly Free when compared to the hybrid baseline (Odds Ratio of 0.715). This essentially confirms that Truly Free applications are less likely to invest in external signaling assets. In the absence of a website, the information asymmetry remains high, forcing the developer to keep the application free. This, in a sense, creates a self-reinforcing circle: low revenue potential prevents costly signaling, and the lack of signaling prevents higher-revenue potential models.

However, the ad-supported model, when compared to Hybrid, has shown a bit different and nuanced set of results. Ad-Supported application has shown positive association with website presence ($\beta = +0.226, p < 0.001$) with Odds Ratio of 1.253. This essentially means that having a website makes an app 25% more likely to be ad-supported than a Hybrid.

It is possible to assume that Ad-supported applications, quite often in the mobile apps ecosystem, are extensions of their existing websites. For these applications, the website is probably not a signal, but rather the parent product itself. Thus, while the Free + ads pricing model would align with low barriers, the existence of a website might be more structural than a strategic choice. But further research to confirm this assumption is recommended. Social proof signals: Review Volumes and Rating Scores

In the digital marketplace, reputation serves as one of the most critical mechanisms to reduce consumer uncertainty, where this dynamic is captured in the Variables Log(Review Count) and Average Rating. Empirical analysis suggests that both the volume of ratings and the perceived quality of the application (average rating) are acting as a powerful filter against the selection of lower barrier models, such as Truly Free or Ad-Supported Strategies, compared to the Hybrid baseline. For Truly Free apps, the odds ratio for Log(Review Volume) is 0.826 ($\beta = -0.141, p < 0.001$), while the Odds Ratio for average star rating is even lower at 0.869 ($\beta = -0.192, p < 0.001$). Similarly, ad-supported apps exhibit Odds Ratios of 0.98 ($\beta = -0.02, p < 0.001$) for Log(Review Volume) and 0.91 ($\beta = -0.095, p < 0.001$) for star rating.

The statistical evidence suggests a quite clear story about the market evolution. Since all Odds Ratios are below 1, every increase in average rating or in volume of rating significantly reduces the likelihood that the application will remain Truly Free or Ad-Supported. Instead, higher-rated applications are essentially pulled towards the Hybrid pricing model. This empirical evidence essentially confirms that the complex hybrid strategy is the domain of market incumbents – applications that are already established in the market, and have already won the trust of the user base. On the other hand, the applications that have lower ratings or insufficient review volume are essentially forced to adopt the monetization models that have lower barriers in order to attract a user base who might be skeptical of their quality.

4.2.2 Testing H_{1b}: Signalling Value for Premium models

The hypothesis H_{1b} suggests that strong signalling would be positively associated with Paid and Freemium models to reduce the information asymmetry between the developers and consumers. The results present a bit of a nuanced support to the hypothesis, revealing a contrast between the signals that users see before purchasing/downloading an application (i.e., description) and signals that users provide after purchasing/downloading an application (i.e., ratings).

Description Length: The "Justification of price" vs "Experience". The variable Log(Description Length) has revealed a strategic distinction between Paid and Freemium pricing models in the iOS mobile application market.

Regarding the paid pricing model, the results strongly support the hypothesis for Paid apps. The empirical results indicated an odds ratio of 1.687, indicating that a 1-unit increase in Log (Description length) makes an application 68.7% more likely to be Paid than Hybrid. This is mainly because Paid apps need an upfront financial commitment from the users. Therefore, it poses the highest possible risk before buying an application. In the absence of a free trial, the application's text description becomes a primary source of information to mitigate this risk. Developers are forced to substitute the application's experience or trial for a description of it.

To the contrary, for freemium applications, the Odds Ratio is 0.851, indicating that a 1-unit increase in Log(Description Length) decreases an application's odds by 14.9% to be freemium than when compared to the Hybrid baseline. These empirical results essentially contradict the assumption that all premium models require lengthy descriptions. Since Freemium apps allow users to download and test the product for free ("experience goods"), the description becomes less critical. The free entry point serves as a sufficient signal for users, lowering potential search costs and reducing the need for the extensive persuasive text required by paid or more complex Hybrid apps.

The "Hybrid Ceiling": Ratings and Websites. While the hypothesis was that the Freemium and Paid app models would have the highest reputation signals, analysis of the variable Log(Review Count) and the dummy variable Has_Website suggests that hybrid apps, not Paid or Freemium, represent the Super-signalers of the market.

Talking about Log(Review Count), both Paid and Freemium models lag significantly behind the Hybrid baseline. The odds Ratio for Log(Review Count) is 0.83 ($\beta = -0.1828, p < 0.001$) for Paid apps, while the odds ratio for Freemium applications is 0.829 ($\beta = -0.187, p < 0.001$). This implies that as Log(Review Count) increases by 1 unit, an app is roughly 17% less likely to use a Paid or Freemium monetization strategy, as it is pulled more towards the Hybrid pricing category. This validates the view that the Hybrid model is, in a sense, an "endgame" strategy, with apps moving towards it. It requires a massive scale and social proof of a user base to be functioning, while Paid and Freemium pricing models are often used by niche or transitional apps that have not yet achieved that level of development.

Regarding the presence of the Website, the difference is even more pronounced here. For Paid applications, the variable has_website has an odds ratio of 1.1, indicating that the odds of being Paid increase by 10% if an application has a website, compared to the Hybrid baseline. However, for

Freemium apps, the Odds ratio drops to 0.539, indicating they are 46.1% less likely to have a website. This exposes a potential Legitimacy Gap for Freemium applications in the iOS universe. While paid applications are maintaining a website, indicating their long-term commitment, the Freemium application is neglecting this costly signal. This suggests that many Freemium applications are relying more on store visibility than on building a dedicated website, which could be a potential strategic weakness.

Maintenance and Application's Lifecycle as a Signal. Lastly, Log(Days Since Update) and Log(App Age) were analyzed to examine signals of developer commitment and the product lifecycle.

When analyzing the Log(Days Since Update) variable, it was found that the Paid strategy shows a significant positive association with the application's staleness. The odds Ratio for Log(Days Since Update) is 1.113 ($\beta = 0.107, p < 0.001$). This indicates that a 1-unit increase in Log(Days Since Update) would increase the odds of an app being Paid rather than Hybrid by 11.3%. This, in a sense, confirms the structural distinction. Based on results, it seems that in the iOS universe, developers treat paid apps as finished goods and that they require less frequent maintenance. In contrast, it seems that Hybrid applications must remain frequently updated to sustain their recurring revenue model (Ads + IAPs) and retain their active user base.

Slightly contrary, Freemium Apps also show a positive, but smaller association with apps' staleness, having the variable's Log(Days Since Update) Odds Ratio value of OR=1.018, ($\beta = 0.017, p < 0.001$), suggesting that they are in the middle ground between the static paid model and the more dynamic Hybrid.

Looking into the potential Legacy effect of an app age, the Log(App Age) variable reveals a significant difference between Freemium Apps and Paid, compared to the Hybrid baseline. Paid apps show one of the strongest effects in the entire model here, with an Odds Ratio of 2.141 ($\beta = 0.761, p < 0.001$). However, for the Freemium applications, Log(App Age) is not statistically significant, making it indistinguishable and not statistically significant from the Hybrid baseline ($\beta = 0.017, p > 0.05$).

Essentially, these findings characterize the Paid model as a Legacy Strategy, while there is no significant age difference to distinguish whether the application is Freemium or Hybrid. These findings confirm that the older the application (the higher log-age), the more likely it is to be paid than a Hybrid. This reflects a historical evolution of the App Store: older applications are set to be stuck with the paid monetization model. Conversely, the fact that the odds ratio of Freemium apps is nearly 1.0, relative to hybrid, indicates that Freemium and Hybrid monetization strategies share the same age profile. They are both modern and evolving strategies.

4.3 Comparative Analysis: The Android Ecosystem

To determine whether the findings for the iOS App Store are universal, we have replicated Multinomial Logit (MNL) on the Android dataset (N=47102). As seen in Annex 4, the Android model achieved a strong goodness-of-fit (Pseudo R-squared = 0.252), allowing direct comparison with the iOS results.

The Hybrid monetization was kept as a baseline due to several reasons. Firstly, it was to ensure the selection of the same variables along with the model for iOS, allowing for direct comparison. Secondly, a Hybrid monetization strategy was kept as a baseline, as it is also a market-dominant strategy in the Android ecosystem, as seen in Table 2. The full results of the MNL model for Android are presented in Annex 3.

4.3.1 Testing H_{1a}: Reducing Barriers in High-Asymmetry Contexts

Hypothesis H_{1a} predicted that high information asymmetry would drive developers toward low-barrier entry models, such as Truly Free or Ad-supported. On Android, this effect is not only present but also more pronounced than on iOS.

Description Length Analysis. The findings of the empirical research indicate that the penalty for having shorter descriptions is far more severe on Android, when compared to iOS. The Odds Ratio of Log(Description Length) for Truly Free apps is 0.369 ($\beta = -0.998, p < 0.001$), compared to 0.491 on iOS. Similarly, for Ad-supported apps, the OR measure is 0.482 ($\beta = -0.731, p < 0.001$).

The empirical findings show that while iOS developers can survive with moderate descriptions in the Free category, the Android market treats low-information apps as inferior ones. A one-unit increase in Log(Description Length) would make an Android app 63% less likely to be Truly Free than Hybrid. This, in a sense, suggests a Lemons Equilibrium for the bottom of the Android market. If a developer cannot produce a lengthy description, the market effectively would force the price to zero.

Website Presence: The Legitimacy Gap Widens. The findings on Android show that the lack of a website is a devastating signal for Android. For Truly Free apps, the variable has_website has the Odds Ratio of 0.407 ($\beta = -0.898, p < 0.001$), which is much lower than the iOS OR of 0.715. Regarding the Ad-supported applications, they were much more likely to have websites on iOS

(OR=1.253, $\beta = -0.226, p < 0.001$), while on Android, they are significantly less likely to have websites (OR=0.804)

In general, these empirical findings indicate the structural difference in the Ad-Supported category. On iOS, “Ads” often imply some sort of content. However, based on OR results, on Android, the data points to minimal utility software, seen more as low-effort, isolated applications that lack a website presence and monetize solely through passive ad views.

Reputation Signals: Ratings scores. Empirical findings for Android are consistent with low-barrier models. The Odds ratio for Average Rating is 0.809 ($\beta = -0.2128\ p < 0.001$) for Truly Free and 0.882 ($\beta = -0.126, p < 0.001$) for Ad Supported, when compared to the Hybrid baseline.

The findings indicate that poorly rated applications cannot sustain a Hybrid monetization model on both Android and iOS ecosystems. However, lower OR on Android suggests that user feedback is an even stricter filter for applications, essentially meaning that low-quality applications are more aggressively pushed out of the Hybrid category.

4.3.2 Testing H_{1b}: The Legacy Distortion in Premium Models

When testing for H_{1b}, it has revealed a difference between two platforms regarding the social proof. While the iOS analysis identified Hybrid apps as the market’s Super-Signallers (even passing Paid apps in rating volume, the Android data presents a different anomaly. On Android, Paid applications surpass Hybrid apps in accumulated review volume. However, as empirical evidence shows, it is more a matter of historical rating accumulation than a sign of current trends.

A) Description Length: The Universal Price Signal

The Description length rule applies globally: Paid apps on Android have a positive association with description length, where variable Log(Description Length) has shown an Odds ratio of 1.26 ($\beta = 0.23, p < 0.001$). Although the effect is slightly weaker than on iOS (OR=1.687), the economic logic remains identical. Regardless of the platform, developers cannot convince a user to pay an upfront price for an application without substantial textual information.

For Freemium applications, the description signal shows little difference as variable Log(Description Length) has the Odds Ratio of OR=0.915, ($\beta = -0.089, p < 0.001$). This finding confirms that the free-to-download-and-try entry point serves as a substitute for description-based signaling on both iOS and Android platforms.

B) The Social proof

This has shown the. Most significant divergence in the comparative analysis, marked by a complete change in coefficient signs for rating volume

Empirical research on iOS, as discussed before, has indicated that higher review counts make an application less likely to be paid, as shown by the Log(Review Count) variable, which yields an odds ratio of 0.83 ($\beta = -0.183, p < 0.001$), positioning Hybrid as a higher-volume dominant strategy. However, quite differently for Android, higher review counts make apps more than twice likely to be Paid as the variable Log(Review Count) variable yields an odds ratio of 2.11 ($\beta = -0.747, p < 0.001$).

These results on Android mainly stem from the fact that the Paid category is dominated by legacy applications, which were once paid for in the early Android era. They have accumulated a large number of reviews over 10+ years. Unlike on iOS, where the Paid model is often used for niche Pro tools with lower volume, the Android Paid market is more like a museum for historically massive apps. Also, an additional assumption: the visible divergence might stem from the fact that on Android, there is a control variable for the number of downloads, while the iOS App Store does not display that information publicly.

C) The Extinction of New Paid Apps

Empirical research has shown that an App's age is a significant factor for an app developer in adopting the paid pricing model. For Android, the Odds Ratio for the Paid application (Variable Log(App Age)) is 3.960 ($\beta = +1.376, p < 0.001$), while it is nearly twice the iOS effect (OR=2.14, $\beta = 0.761, p < 0.001$). This shows that on iOS, the paid pricing model is in a sense a legacy strategy, while for Android, it is much more like an extinct strategy for new entrants. An increase by one unit in Log (App Age) makes an Android application nearly 4 times more likely to be paid. This confirms that the high review volume indicated in the section above is purely a legacy artifact. New developers launching an application in the Android ecosystem today cannot adopt a paid pricing model and should shift towards a Freemium or hybrid monetization strategy.

4.3.3 Summary of Key Cross-Platform Divergences

As Table 3 summarizes, the key Cross-Platform Divergencies, which are seen in such signals as having a website. Also, for Paid applications, Log (Review Count) and Log (App Age) show the different outcomes between the Android and iOS platforms.

Table 3
Summary of Key Cross-Platform Divergences

Variable	iOS Dynamic	Android Dynamic	Economic Implication
Paid Log(Review Volume)	Low (OR 0.83)	Very High (OR 2.11)	iOS Paid market is niche; Android Paid market is dominated by famous "Legacy Giants."
Paid Log(App Age)	Old (OR 2.14)	Ancient (OR 3.96)	The "Paid" model is structurally obsolete for new Android launches.
Website Signal (Has_Website)	Universal Premium Signal	Hybrid-Exclusive Signal	On Android, having a website is the specific marker of the Hybrid Monetization strategy, while for iOS it is it is common signal for Paid and Hybrid monetization strategies

Source: compiled by the author, based on the empirical analysis

4.3.4 Synthesis of Findings for Model 1

Synthesizing empirical evidence from both ecosystems, they provide a similar result, as the MNL regression analysis result failed to reject the $\boldsymbol{H_{1a}}$ across both ecosystems. The Research Question was: How do varying degrees of information asymmetry between mobile application developers and consumers impact the selection of different pricing models within the mobile application marketplace?

Low Signals Favor Low Barriers (Fail to Reject H_{1a}): In both Android and iOS, MNL models show that developers facing high information asymmetry and unable to signal the quality of an application are significantly more likely to choose Ad-Supported or Truly Free models over the Hybrid baseline to minimize consumer risk.

Essentially, in the iOS ecosystem, the description length acts as a signal. Longer descriptions significantly reduce the likelihood of choosing the ad-supported model (OR=0.5, $\beta = -0.687, p < 0.001$). A similar outcome holds for Android (OR=0.48, $\beta = -0.731, p < 0.001$). This confirms that, in situations where developers lack the capacity to signal quality through descriptive depth, they lower the financial barrier to zero.

Looking through the information asymmetry point of view, such a strategy mitigates the problem of Adverse Selection (Akerlof, 1970), which is inherent in markets, lacking transparency. By eliminating the upfront payment to download the application, the developer essentially transfers the risks from the consumers to themselves. This, in a sense, prevents market failure, which might occur if users, who fear the "lemon" application, refused to pay the upfront price.

Signalling Through Description (Fail to Reject H_{1b}): The empirical analysis found partial, but distinct support regarding Paid applications. On both platforms, Paid strategies were positively associated with longer description lengths (*iOS: OR=1.69* $\beta_{iOS} = 0.52\ , p < 0.001$; *Android*: OR=1.26, $\beta_{Android} = 0.23\ , p < 0.001$;). This suggests that the developers of Paid applications are attempting to bridge the information gap by investing heavily in descriptive signalling. However, unlike what was hypothesized, the Hybrid model (the baseline) appeared to be the favourable strategy of choice for the applications that have the highest reputation (high ratings) and have a website. For instance, having a website has significantly reduced the likelihood of choosing Freemium ($\beta_{iOS} = -0.62\ , p < 0.001$, *OR=0.54*) or Paid ($\beta_{Android} = -0.31\ , p < 0.001$, *OR=0.74*) strategies relative to the baseline. These findings essentially suggest that a Hybrid monetization strategy is the true high-quality equilibrium in the modern mobile applications market.

Looking from the information asymmetry point, this dominance suggests that the Hybrid monetization model is essentially offering a more effective solution to the " Experience Goods" (Nelson, 1970) paradox, when compared to Paid models. Specifically, the high-quality developers minimize the risk of adverse selection by reducing the initial barrier to entry while using clear signals, such as description length or a website, to signal the quality.

4.4 Model specification and fit for Model 2

The regression models, run on both platforms, have demonstrated statistical robustness, though with varying degrees of explanatory power due to platform-specific data availability.

For the iOS ecosystem as seen in Annex 6, the model explains approximately 54.6% of the variance in rating counts, as the adjusted R^2 shows a coefficient of 0.546. Diagnostic tests for multicollinearity (VIFs) indicate no severe issues, with almost all VIFs remaining below 2.4.

For the Android ecosystem as seen in annex 8 the model fit is notably higher, explaining 84.4% of the variance (adjusted $R^2 = 0.844$). This increase in explanatory power is mainly due to the availability and inclusion of the Installs dummy variable, which is available only in the Google Play dataset. These variables serve as direct proxies for user base size, strongly correlating with the dependent variable.

4.4.1 iOS Analysis

The analysis of iOS data has provided insights into how barriers to entry might operate in the iOS model. In the model, as mentioned before, the Hybrid strategy serves as the baseline reference category, since it is a market-dominant strategy and deviations from market norms are analyzed. The full results for the OLS regression for iOS are presented in Annex 5.

A) Independent Variable – Pricing Strategy.

The coefficient for the Paid strategy is negative and statistically significant for log (rating count), with $\beta = -0.851$ (p<0.001). This indicates that, holding quality and information signals constant, applications requiring an upfront payment accumulate significantly fewer ratings than Hybrid applications. This finding might be slightly different if download count data were available and the application's popularity could be controlled for. However, based on the model, this finding implies that the theory of information asymmetry holds: an upfront payment prevents users from trying the product and evaluating it, creating a financial gate that limits the accumulation of social proof.

The Freemium strategy in the iOS ecosystem has shown a statistically significant negative Beta coefficient ($\beta = -0.838,\ p < 0.001$). The results are interestingly quite similar to the Paid strategy. This suggests that Freemium (only IAP, no ads) does not guarantee the same level of engagement as the Hybrid model, as users seem less inclined to provide ratings and social proof for the application.

Regarding the Ad-Supported strategy, relying solely on ads as the developer's monetization method does not show a statistically significant difference compared to the Hybrid baseline ($\beta = -0.069, p = 0.179$. This lack of significance is a positive finding – Ad-supported applications generate rating volumes that might be compatible with the high-performing Hybrid baseline.

B) Control Variables:

The control variables also consider some of the information asymmetry narrative, that is being controlled in the model, for instance, Log(Description Length) ($\beta = 0.317, p < 0.001$) is positively related to the rating volume, meaning that search costs are reduced through detailed description, thus leading to the higher adoption of the application. Similarly, a proxy for an application's complexity, App's Size variable Log (Size in MB), is strongly positive ($\beta = 0.491, p < 0.001$), meaning that users are willing to provide feedback to heavy applications. Also, based on personal experience, these heavier applications are more likely to include triggers and notifications asking them to rate the application.

C) Implication for iOS:

The hierarchy for market stability and application's popularity, based on the model run, seems clear: the Hybrid strategy is among the best for accruing the rating count. The hierarchy stands as follows: Hybrid ≈ Ad-Supported > Freemium ≈ Paid > Truly Free. The data suggests that strategies involving advertising, either alone or combined with IAPs, are superior at reducing potential frictions and generating the feedback volume necessary for revenue stability in the app market. However, for further research, additional data and variables of revenue per application should be considered as potential controls and download measures.

4.4.2 Comparative Analysis on Android Ecosystem

When analyzing the Android Ecosystem, it presented a contrasting dynamic, heavily influenced by the inclusion of multiple download tiers. As this Model 2 controls for the number of installs, the strategy coefficients here measure the propensity of users to rate and evaluate the application, rather than total market acquisition. The full results for the OLS regression for Android are presented in Annex 7.

A) Independent Variable – Pricing Strategy

Unlike the hypothesis that the Paid strategy has the largest barrier to entry, it has been shown that this strategy exhibits a significant, positive coefficient ($\beta = 0.874, p < 0.001$) in rating the application, compared to the hybrid baseline. This implies that, given the same number of downloads, users who pay for a download of an application are significantly more likely to provide a rating for an application than users of free apps. This could be attributed to the fact that users who cross the initial barrier to entry with an upfront cost are more committed and more likely to be vocal about the quality of an application.

However, this engagement of Paid app users must be assessed alongside the install-control dummy variables. The massive negative coefficients associated with the lower download tiers might indicate that while Paid users are active, Paid apps struggle to achieve high install tiers, which are needed to ensure revenue stability.

The Freemium strategy also outperforms the Hybrid baseline in terms of engagement intensity ($\beta = 0.192, p < 0.001$). However, Ad Supported ($\beta = -0.349, p < 0.001$) and Truly Free ($\beta = -0.586, p < 0.001$) strategies are showing significantly lower user engagement to evaluate the application's performance. This suggests that while Ad-Supported and Truly Free applications are acquiring a significant user base due to a low barrier to entry, those users are less engaged and less likely to leave feedback and improve the application's social proof score in rating count, compared to applications that involve payments, like Freemium or Paid applications.

B) Control Variables for Android model

Interestingly, variable Log(Description Length) ($\beta = 0.491, p < 0.001$) plays a more minor role on Android when compared to iOS. This coefficient suggests that Android users rely less on textual descriptions and more on other signals, such as Install count, when deciding whether to download an application. Also, Rating, which signals the quality of an application) remains the dominant information signal to users about whether to download an application and leave feedback.

4.4.3 Synthesis of Findings for Model 2

Integrating and combining empirical evidence from both ecosystems, they provide a nuanced answer to Research Question 2: To what extent can the implementation of specific monetization strategies mitigate market uncertainty and enhance revenue stability for mobile application developers?

The evidence provides a bit of a split verdict on the Hypothesis, which stated that lower entry barriers would increase rating counts:

iOS ecosystem – Partial support for H_2: On the iOS Ecosystem, the results partially supported the Hypothesis. The OLS model showed that Paid strategies had a significant negative impact on the log(rating volume) dependent variable ($\beta = -0.851, p < 0.001$), compared to the Hybrid baseline. It indicates that the Paid model acts as a significant barrier to adoption, with a strong negative association with rating volume. However, being a free application is not a solution. Applications, using Freemium ($\beta = -0.84, p < 0.001$) and Truly Free ($\beta = -0.90, p < 0.001$) monetization strategies, performed poorly and have shown a statistically significant negative relationship to rating count when compared to Hybrid Baseline. However, Hybrid and Ad-Supported models, which allow free entry and monetize through ads (and IAPs for Hybrid), significantly outperform the paid model, suggesting that the upfront cost to download an application is acting as a friction point. This leads to the situation that applications fail to achieve the critical mass of users needed for revenue stability. Therefore, the findings suggest that revenue stability on the iOS platform is not achieved simply by offering an application to download for free. It is more related to implementing a Hybrid monetization model (or as findings indicate – Ad-Supported) that mitigates consumers' risk before downloading an application. Since these models do not have a financial upfront cost to download, it allows users to resolve information asymmetry through direct experience, or trial, rather than depending on a costly and financial signal. Eventually, this approach solves for the potential Akerlof's (1970) "Lemons" problem by effectively dropping the cost of experimentation and trial to zero.

Android - reject H_2. The Android market analysis yielded slightly different results than iOS, as the model controlled for the number of downloads. Paid strategies were associated with the highest rating counts ($\beta = 0.87, p < 0.001$) relative to the Hybrid baseline. The next is followed by a Freemium ($\beta = 0.19, p < 0.001$) monetization model. However, Ad-Supported ($\beta = -0.35, p < 0.001$) and Truly Free (($\beta = -0.59, p < 0.001$) models have significantly lower rating counts. This suggests that on Android, a price tag might act as a trusted quality filter, which attracts a user base that is more engaged, whereas on iOS, a price tag acts more as a barrier to entry. However, it is needed to keep in mind that, based on findings in Model 1, the paid monetization model is prevalent for old applications.

From the perspective of Information Asymmetry, this finding suggests that users in the Android ecosystem rely on a price as a Screening Mechanism (Stiglitz & Weiss, 1981) to address the potential "Lemons" problem. In a market that is flooded with low-quality and free applications, users might identify the upfront price not as a financial barrier, but more like a credible signal of value. Consequently, the price tag for an application act as a clear signal of quality. By requiring an upfront payment, the developers filter out casual users and attract a committed audience, who create a more stable user base than free models.

4.5 Strategic Implications and Recommendations

Based on empirical analysis of the iOS market and a comparative analysis of the Android market, four key strategic recommendations have been derived for mobile application developers. These recommendations address the management of information asymmetry to optimize the selection of monetization models in a dual-platform ecosystem.

4.5.1 The Legacy Model of Pay-to-Download

The empirical evidence suggests that the paid model is effectively extinct for new entrants on Android. The odds ratio for Log (app Age) (OR=3.96) relative to Hybrid, indicates that the Android Paid apps market is dominated by the legacy applications with a high number of reviews accumulated (OR=2.11 for Log(Review Count))

The recommendation for developers launching an Android application is to avoid the pay-to-download pricing model strictly. The market structure forces new entrants to choose between a Freemium (For User Acquisition) and a Hybrid (for monetization) pricing strategy. Attempting to launch a paid application on Android is essentially fighting against the prevailing market trends.

On iOS, the app age effect is similar to Android's in some respects, but it is much weaker (OR=2.14) and the reliance on description length is stronger (OR=1.69) compared to the Hybrid baseline. This suggests that the Paid strategy remains a more viable option on iOS, when compared to Android, but the developers must invest heavily in textual signaling (i.e., description) to justify the upfront cost.

Therefore, the recommendation for iOS developers is still to avoid the Pay-to-Download pricing model. However, if a developer must launch a paid application, the suggestion is to signal the application's quality through a textual description to justify the user's upfront cost.

4.5.2 The Hybrid Ladder: Scaling into the Complexity

Even though the Hybrid (Ads + IAP) model emerges as a dominant strategy to maximize revenue, cross-platform data analysis reveals that it imposes the highest signaling barriers to entry, due to the compounded information asymmetry that requires users to bear both attention costs through ads and financial costs through IAP.

The data indicate that demand for social proof as a mitigating signal is evident, though its intensity varies by platform. For instance, on iOS, Hybrid applications are statistically associated with significantly higher review volumes than any other category. Specifically, the odds of an application having high review volumes are lower for Paid (OR=0.83) and Freemium (OR=0.84) than for the Hybrid baseline. This indicates that on iOS, the Hybrid model is a characteristic of an established high-trust application.

On Android, the story takes an interesting turn. At first glance, Paid applications seem to dominate review accumulation (OR=2.11). However, this figure might be deceptive; it is primarily influenced by the application age variables, where legacy and ancient applications have already accumulated a larger number of downloads and rating volumes. This nuance actually highlights the true strength of the Hybrid model: while Paid apps rely on small-scale successes, Hybrid remains the superior engine for sustaining social proof at scale. Similarly, Freemium apps perform favorably (OR=1.15), serving as a natural stepping stone toward that robust Hybrid monetization model.

Therefore, the strategic recommendation for developers is to treat the Hybrid model more like an endgame strategy than a launch, as it functions best when supported by massive social proof.

- **Phase 1 – Launch and acquisition:** Adopt a Freemium or Ad-Supported model to lower entry barriers and accumulate the critical mass of ratings required by the market
- **Phase 2 – Pivot and Monetization:** Once Social Proof for the application is established, developers should introduce more complex hybrid monetization layers. Attempts to monetize via both

Ads and IAP from launch, without a trust signal like a high rating, might risk alienating users who perceive the aggressive monetization strategy as unjustified for an unproven application.

A) Hybrid Model for Revenue Stability

The analysis of Model 2 points to the Hybrid monetization model as the optimal strategy for developers to maximize the potential revenue stability. By combining low barriers to advertising to attract volume with monetization depth, such as in-app purchases, the Hybrid strategy effectively mitigates the problem of paid ads that might struggle due to the release and the application's low social proof. Also, paid applications still have low engagement traps, which prevent them from having enough social proof.

From a strategic perspective, the Hybrid model also serves as an instrument for second-degree price discrimination, allowing developers to maximize the value for different user bases. By targeting time-rich users through advertising and users willing to pay for IAP, this approach extracts consumer surplus. It ensures that no segment of the user base remains unmonetized.

4.5.3 The Website as a Signal: Escaping the Lemons

The analysis has identified the massive Legitimacy Gap in the Freemium Sector, particularly on Android. Therefore, the data indicate that apps without a website are 60% less likely to be anything other than Truly Free (OR=0.4). Similarly, the Freemium applications across both platforms are significantly less likely to have websites than Hybrid apps.

The strategic recommendation for mobile application developers is to invest resources in developing a professional website, as this presents an opportunity to differentiate themselves as high-quality developers. This is mainly because an average Freemium or Truly Free application might be treated as a "Lemon" without a website and with limited information. By establishing a web presence, a Freemium app's developer signals Hybrid-tier Quality at a Freemium Price. This essentially reduces information asymmetry, which might scare users away from Free apps and also potentially increase conversion rates from Free to Paid users.

5. CONCLUSIONS

5.1 Research Summary and Methodology

The primary objective of this thesis was to investigate the economic dynamics of the mobile application market, specifically with the focus on how asymmetric information between the developers and users would influence the pricing strategy selection and how these strategies subsequently impact market stability.

Research Question 1 (RQ1) asked: How do varying degrees of information asymmetry between mobile application developers and consumers impact the selection of different pricing models within the mobile application marketplace?

Hypothesis 1a ($\boldsymbol{H_{1a}}$) posited that high information asymmetry, indicated by the weak signals, would lead the developers to choose Ad-Supported or Truly Free models.

Hypothesis 1b ($\boldsymbol{H_{1b}}$) posited that strong signalling capabilities would be associated with Paid and Freemium models.

Research Question 2 (RQ2) asked: To what extent can the implementation of specific monetization strategies mitigate market uncertainty and enhance revenue stability for mobile application developers?

Hypothesis 2 ($\boldsymbol{H_2}$) posited that free-to-download strategies (Freemium, Ad-Supported, Truly Free) would result in significantly higher rating counts (a proxy for stable app adoption) compared to Paid applications.

To address these research questions and test the hypothesis, this study employed a dual-methodological approach by using large-scale datasets collected from publicly available information for the Apple App Store (iOS) (N=94900) and the Google Play Store (Android) (N=47096). RQ1 was analysed using Multinomial Logit (MNL) regression analysis, calculating the probability of a developer choosing a specific strategy relative to the market-dominant Hybrid baseline. RQ2 was analysed using Ordinary Least Squares (OLS) regression, modelling the impact of monetization strategy on Log-Rating count

5.2 Synthesis of Empirical Findings

The empirical analysis has revealed that pricing in the mobile application market is not only a financial decision but also a strategic mechanism to mitigate potential information asymmetry and market entry barriers.

Information Asymmetry and Strategy Selection (RQ1). The MNL regression analysis results failed to reject the $\boldsymbol{H_{1a}}$ across both ecosystems.

Low Signals Favor Low Barriers (Fail to Reject $\boldsymbol{H_{1a}}$). The MNL models confirm that developers, who are facing high information asymmetry, which is defined through weak signals, such as short descriptions, are more likely to select Ad-Supported or Truly Free monetization models. By lowering the financial barrier to zero, these developers resolve the Adverse selection problem (Akerlof, 1970), which is prevalent in opaque markets. This approach allows for the transfer of transaction risk from the consumers to developers, ensuring the adoption when quality signals are too weak to justify an upfront price.

Signalling Through Description (Fail to Reject $\boldsymbol{H_{1b}}$): While applications with a Paid monetization model rely on longer and more informative descriptions, the empirical research identifies to the Hybrid model as a preferred equilibrium for high-reputation developers with strong signals, such as having a website. This suggests that the Hybrid model is a more effective solution to the Experience Goods paradox (Nelson, 1970) than the Paid model. By combining low entry barriers with verified quality signals, the developers minimize the risk of Adverse Selection (Akerlof, 1970), ensuring the market penetration, without sacrificing their revenue potential.

Monetization and market stability (RQ2). The analysis of Research Question 2 uncovered a divergence between the two platforms, offering a nuanced answer to Hypothesis 2

iOS ecosystem – Partial support for $\boldsymbol{H_2}$. On the iOS Ecosystem, the empirical research confirmed that upfront pricing acts as a significant barrier to adoption, as Paid monetization models are underperforming in rating volume. In contrast, Hybrid and Ad-Supported models proved to be a superior strategy for revenue stability. These two models outperformed Paid, Truly Free, and Freemium models by mitigating the consumer's ex-ante risk. This essentially supports the conclusion that eliminating financial barriers enables users to solve for the potential information asymmetry through direct experience. This essentially neutralizes the Lemons Problem (Akerlof, 1970) by lowering the cost of experimentation to zero.

Android - reject $\boldsymbol{H_2}$. In contrast to iOS results, the Android analysis has identified that the Paid monetization model is a driver of the highest rating volume, outperforming Ad-Supported and other free-to-download models. This finding suggested that in the ecosystem, full of low-quality alternatives, the upfront price functions as a Screening Mechanism (Stiglitz & Weiss, 1981) rather than an entry barrier. Therefore, for Android users, see the price tag as a signal of quality, since it is mostly applied to legacy applications. Also, the requirement of payment effectively filters for committed users to ensure better revenue stability.

5.3 Limitations and Future Research

Data Availability and Granularity. A significant limitation of this study lies in the availability and transparency of the data. Neither Apple nor Google publicly displays the proprietary performance data, such as exact revenue figures or precise daily download counts. Only Android has provided some of the available download number data, which is particularly restrictive. Data that was available at the Google Play Store reports adoption volume in broad install buckets (i.e., 1000+, 5000+), rather than providing continuous integers. This lack of granularity meant it was necessary to rely on categorical ranges for control variables, which likely smooths out the finer distinctions in the performance of the application at the lower or upper bounds of these buckets. Because of this lack of granular volume data, this study has used Rating Count as a proxy for market adoption. Consequently, while we can infer from the Rating count what the popularity and user base stability of an application is, a model cannot capture precise revenue metrics, such as the Average Revenue Per User (ARPU) or Return on Investment (ROI). For example, a paid application with fewer ratings, which was a common scenario on iOS, might generate a higher ROI or ARPU than an ad-supported application with a distinctly higher volume and potentially a higher rating count.

Endogeneity in Strategy Selection. Regarding Research Question 1, the specific limitation arises from the cross-sectional design concerning the direction of causality. While the MNL model assumes that information asymmetry proxies are one of the drivers that determine the pricing strategy, in reality, this relationship is likely to be bidirectional (endogenous).

For instance, a developer might not select a paid pricing model simply because they have a long description. Instead of having decided on a monetization strategy, they might be compelled to write a longer description to justify the potential upfront cost for the user. This might create a simultaneity bias, where signals such as description length serve as both a pre-existing signal of quality and a post-decision functional requirement. This creates quite a tangled relationship, which cross-sectional data cannot fully unravel.

Cross-sectional Design. This study uses a cross-sectional design, effectively capturing a static state of the market, rather than a constantly evolving market. Also, it cannot capture the lifecycle of an application, such as a developer launching a paid pricing model and later pivoting to a Hybrid model. This essentially limits the ability to make a causal claim about how changing a strategy affects rating velocity over time, because the data reflect only the strategy in place at the moment the data were collected.

Future Research. As for future research, it should focus on bridging the gaps identified earlier by integrating revenue estimates and granular download data from third-party intelligence firms, such as Sensor Tower or AppTweak. Moreover, adopting a longitudinal panel design would allow the researchers to track strategy pivots as they occur. This is necessary to verify whether the high rating counts observed in Hybrid or Ad-Supported models would actually translate into long-term financial sustainability.

Final Conclusion. In conclusion, this thesis demonstrates that information asymmetry is not just a feature but a defining strategic decision in the mobile application market. Here, the monetization strategy serves as a strategic signaling device. For instance, developers facing high asymmetry rationally lean towards the Ad-Supported models to lower entry barriers. In contrast, the Hybrid model has emerged as the equilibrium for the majority of apps and for high-quality applications as well. Perhaps, most importantly, market stability proved to be platform-dependent. While iOS favors the low-friction accessibility of Hybrid and Ad-Supported applications, Android users reward the explicit quality signal of a Price Tag. Therefore, successful monetization requires not aligning strategy with the product, but also with the distinct economic psychology of the target ecosystem.

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THE INFLUENCE OF INFORMATION ASYMMETRY ON PRICING STRATEGIES IN THE MOBILE APPLICATIONS MARKET

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Master thesis

Strategic Economics: master study programme

Vilnius University, Faculty of Economics and Business Administration

Supervisor – Dr. Tomoyuki Hashimoto

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SUMMARY

58 pages, 17 tables, 89 references

The main purpose of this master's thesis is to investigate the economic dynamics of the mobile application market, focusing on how information asymmetry between the developers and consumers influences the selection of pricing strategies and how these strategies subsequently impact market stability. The study aims to determine whether monetization model choices serve as strategic signals to reduce the trust gap in an economy characterized by "experience goods".

This work consists of several main parts: the analysis of the theoretical literature, the description of the research methodology, the empirical analysis of the iOS and Android ecosystems, strategic recommendations, and the final conclusions.

The literature analysis reviews the development of information asymmetry theories, specifically Akerlof's "Market for Lemons" (1970) and Spence's signalling theory (1973), adapting these frameworks to the mobile application market. In this context, mobile apps are viewed as experience goods with non-observable quality prior to download. It posits that the selection of a monetization strategy is a necessary response to adverse selection, functioning as a critical mechanism to reduce the information gap between developers and users in a crowded app ecosystem.

To achieve the research objective, the author employed a dual-methodological quantitative approach using large-scale datasets from the Apple App Store (N=94,900) and Google Play Store (N=47,096). Multinomial Logit (MNL) regression was used to analyze how developer signals determine the probability of choosing specific pricing strategies. Additionally, Ordinary Least Squares (OLS) regression was utilized to measure the impact of these strategies on rating counts, which served as a proxy for revenue stability

The performed research revealed that pricing is a strategic mechanism used to mitigate information asymmetry. The results indicate that developers facing high asymmetry and weak quality signals are structurally driven to select Ad-Supported or Truly Free models to lower entry barriers and resolve the adverse selection problem. Conversely, the Hybrid model emerged as the equilibrium for developers with strong signalling capabilities. Furthermore, the study uncovered a significant divergence between platforms regarding market stability. On iOS, low-friction models (Hybrid and Ad-Supported) resulted in higher stability, while on Android, the Paid monetization model outperformed others. This suggests that an upfront price tag functions as a necessary quality screening mechanism in that specific ecosystem.

In the conclusion, the author emphasizes that managing information asymmetry effectively requires aligning the monetization strategy not only with the product's attributes but also with the unique economic psychology of the mobile application platform. The findings offer practical guidelines for new market entrants, specifically on how to use pricing strategy as a credible signal of trust to mitigate market uncertainty and ensure long-term survival

INFORMACIJOS ASIMETRIJOS ĮTAKA KAINODAROS STRATEGIJOMS MOBILIŲJŲ PROGRAMĖLIŲ RINKOJE

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SANTRAUKA

58 puslapiai, 17 lentelių, 89 literatūros šaltiniai

Pagrindinis šio magistro darbo tikslas – ištirti mobiliųjų programėlių rinkos ekonominę dinamiką, sutelkiant dėmesį į tai, kaip informacijos asimetrija tarp kūrėjų ir vartotojų veikia kainodaros strategijų pasirinkimą ir kaip šios strategijos vėliau įtakoja rinkos stabilumą. Tyrimu siekiama nustatyti, ar monetizacijos modelių pasirinkimas veikia kaip strateginis signalas, mažinantis pasitikėjimo spragą ekonomikoje, kuriai būdingos „patyriminės prekės" (angl. experience goods).

Šį darbą sudaro kelios pagrindinės dalys: teorinės literatūros analizė, tyrimo metodologijos aprašymas, iOS ir Android ekosistemų empirinė analizė, strateginės rekomendacijos bei galutinės išvados.

Literatūros analizėje apžvelgiama informacijos asimetrijos teorijų raida, ypač G. Akerlofo „Citrinų rinkos" (angl. Market for Lemons) (1970) ir M. Spence'o signalizavimo teorija (1973), pritaikant šiuos teorinius rėmus mobiliųjų programėlių rinkai. Šiame kontekste mobiliosios programėlės traktuojamos kaip patyriminės prekės, kurių kokybės neįmanoma įvertinti prieš atsisiunčiant. Darbe teigiama, kad monetizacijos strategijos pasirinkimas yra būtinas atsakas į neigiamą atranką (angl. adverse selection), veikiantis kaip esminis mechanizmas, mažinantis informacijos atotrūkį tarp kūrėjų ir vartotojų prisotintoje programėlių ekosistemoje.

Tyrimo tikslui pasiekti autorius taikė dvejopą kiekybinį metodą, naudodamas didelės apimties duomenų rinkinius iš „Apple App Store" (N=94 900) ir „Google Play Store" (N=47 096). Multinominė logistinė (MNL) regresija buvo naudojama analizuoti, kaip vystytojų signalai lemia konkrečių kainodaros strategijų pasirinkimo tikimybę. Be to, taikant mažiausių kvadratų (OLS) regresiją, buvo vertinamas šių strategijų poveikis reitingų skaičiui, kuris naudotas kaip pajamų stabilumo rodiklis.

Atliktas tyrimas atskleidė, kad kainodara yra strateginis mechanizmas, naudojamas informacijos asimetrijai švelninti. Rezultatai rodo, kad kūrėjai, susiduriantys su didele asimetrija ir silpnais kokybės signalais, yra struktūriškai skatinami rinktis reklama paremtus (angl. Ad-Supported) arba visiškai nemokamus (angl. Truly Free) modelius, siekiant sumažinti įėjimo barjerus ir spręsti neigiamos atrankos problemą. Priešingai, hibridinis modelis išryškėjo kaip pusiausvyros taškas kūrėjams, turintiems stiprius signalizavimo gebėjimus. Be to, tyrimas atskleidė reikšmingą skirtumą tarp platformų rinkos stabilumo atžvilgiu. „iOS" platformoje mažų barjerų modeliai (hibridinis ir reklama paremtas) lėmė didesnį stabilumą, tuo tarpu „Android" platformoje geriausius rezultatus

demonstravo mokamas (angl. Paid) monetizacijos modelis. Tai rodo, kad toje konkrečioje ekosistemoje išankstinė kaina veikia kaip būtinas kokybės filtravimo mechanizmas.

Išvadose autorius pabrėžia, kad efektyvus informacijos asimetrijos valdymas reikalauja monetizacijos strategiją derinti ne tik su produkto savybėmis, bet ir su unikalia mobiliųjų programėlių platformos ekonomine psichologija. Tyrimo išvados pateikia praktines gaires naujiems rinkos dalyviams, ypač apie tai, kaip naudoti kainodaros strategiją kaip patikimą pasitikėjimo signalą, siekiant sumažinti rinkos neapibrėžtumą ir užtikrinti ilgalaikį išlikimą.

7. ANNEXES

Annex 1: Multinomial Logit Regression Results: Determinants of Pricing Strategy Selection (iOS Ecosystem)

Table 4

*MNL Parameter Estimates: **Ad Supported** Strategy vs. Hybrid Baseline (iOS)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	-9.6341	1.00E-04	***	< 0.001	0.2656
Average Rating (1-5)	-0.0948	0.9096	***	< 0.001	0.0179
Log(Review Count)	-0.0201	0.9801	*	0.0332	0.0094
Log(Description Length)	-0.6866	0.5033	***	< 0.001	0.0316
Name Length (Chars)	-0.0322	0.9683	***	< 0.001	0.0033
Has Website (Yes=1)	0.2255	1.253	***	< 0.001	0.063
Log(Days Since Update)	-0.3211	0.7254	***	< 0.001	0.0157
Log(App Age)	-0.018	0.9822		0.4695	0.0249
Log(Size in MB)	0.282	1.3257	***	< 0.001	0.0289
Country: DE	-0.416	0.6597	***	< 0.001	0.0718
Country: FR	-0.4213	0.6562	***	< 0.001	0.0727
Country: GB	-0.3946	0.6739	***	< 0.001	0.0688
Category: Business	13.0361	458665.5874	***	< 0.001	0.118
Category: Developer Tools	-4.9088	0.0074	***	< 0.001	0
Category: Education	10.8707	52612.84	***	< 0.001	0.2035
Category: Entertainment	12.2445	207824.9937	***	< 0.001	0.1195
Category: Finance	14.6109	2215409.18	***	< 0.001	0.0841
Category: Food & Drink	15.0513	3441186.273	***	< 0.001	0.1119
Category: Games	10.046	23063.9269	***	< 0.001	0.1207
Category: Graphics & Design	10.4443	34348.4252	***	< 0.001	0.4817
Category: Health & Fitness	12.1338	186054.7752	***	< 0.001	0.1279
Category: Lifestyle	12.6252	304139.2318	***	< 0.001	0.1101
Category: Magazines & Newspapers	-4.1225	0.0162	***	< 0.001	0
Category: Medical	12.7926	359563.4572	***	< 0.001	0.1775
Category: Music	11.8353	138034.2226	***	< 0.001	0.2193
Category: Navigation	12.3205	224243.1605	***	< 0.001	0.1737
Category: News	11.7207	123097.0253	***	< 0.001	0.2656
Category: Photo & Video	10.5314	37473.3253	***	< 0.001	0.2456
Category: Productivity	10.3071	29944.5704	***	< 0.001	0.2708
Category: Reference	-27.1392	0	NA	NA	NaN
Category: Shopping	16.1429	10251563.06	***	< 0.001	0.0846
Category: Social Networking	9.0995	8951.2115	***	< 0.001	0.6775
Category: Sports	12.2322	205304.4537	***	< 0.001	0.1682

Continuation of Table 4

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Stickers	-4.4906	0.0112	***	< 0.001	0
Category: Travel	14.7571	2563985	***	< 0.001	0.0778
Category: Utilities	12.0662	173892.9209	***	< 0.001	0.0963
Category: Weather	11.203	73351.0845	***	< 0.001	0.3447

Source: Compiled by the author based on Multinomial Logit regression analysis of the iOS dataset.

Table 5

*MNL Parameter Estimates: **Truly Free** Strategy vs. Hybrid Baseline (iOS)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	-6.2848	0.0019	***	< 0.001	0.1972
Average Rating (1-5)	-0.1916	0.8256	***	< 0.001	0.0122
Log(Review Count)	-0.1407	0.8688	***	< 0.001	0.008
Log(Description Length)	-0.7106	0.4913	***	< 0.001	0.0228
Name Length (Chars)	-0.07	0.9324	***	< 0.001	0.0025
Has Website (Yes=1)	-0.3355	0.715	***	< 0.001	0.0419
Log(Days Since Update)	-0.2242	0.7992	***	< 0.001	0.0113
Log(App Age)	0.1226	1.1304	***	< 0.001	0.0186
Log(Size in MB)	0.2678	1.3071	***	< 0.001	0.0203
Country: DE	-1.4286	0.2396	***	< 0.001	0.0568
Country: FR	-1.4492	0.2348	***	< 0.001	0.0576
Country: GB	-1.1939	0.303	***	< 0.001	0.0534
Category: Business	12.992	438902.7814	***	< 0.001	0.068
Category: Developer Tools	-5.8704	0.0028	***	< 0.001	0
Category: Education	10.4721	35315.3728	***	< 0.001	0.0996
Category: Entertainment	9.9992	22009.5963	***	< 0.001	0.1295
Category: Finance	13.6866	879046.7706	***	< 0.001	0.07
Category: Food & Drink	13.0142	448738.2363	***	< 0.001	0.126
Category: Games	8.2397	3788.4758	***	< 0.001	0.1216
Category: Graphics & Design	-45.517	0	NA	NA	NaN
Category: Health & Fitness	11.2254	75008.9527	***	< 0.001	0.0911
Category: Lifestyle	11.5964	108708.6739	***	< 0.001	0.0805
Category: Magazines & Newspapers	-4.3976	0.0123	***	< 0.001	0
Category: Medical	12.5614	285341.262	***	< 0.001	0.0953
Category: Music	9.4329	12493.224	***	< 0.001	0.2861
Category: Navigation	11.8889	145636.0083	***	< 0.001	0.0939
Category: News	8.5859	5355.4942	***	< 0.001	0.4352
Category: Photo & Video	9.1308	9235.7523	***	< 0.001	0.1956
Category: Productivity	10.1449	25461.1105	***	< 0.001	0.1248
Category: Reference	10.0153	22366.8008	***	< 0.001	0.2079

Continuation of Table 5

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Shopping	14.1796	1439190.447	***	< 0.001	0.0848
Category: Social Networking	9.9416	20776.2858	***	< 0.001	0.1784
Category: Sports	10.4543	34692.8481	***	< 0.001	0.149
Category: Stickers	12.5628	285716.4295	***	< 0.001	0.5864
Category: Travel	13.1121	494915.5814	***	< 0.001	0.0705
Category: Utilities	10.7439	46348.6857	***	< 0.001	0.0706
Category: Weather	9.0979	8936.6268	***	< 0.001	0.3468

Source: Compiled by the author based on Multinomial Logit regression analysis of the iOS dataset.

Table 6

*MNL Parameter Estimates: **Paid** Strategy vs. Hybrid Baseline (iOS)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	-9.5284	1.00E-04	***	< 0.001	0.3657
Average Rating (1-5)	-0.0082	0.9918		0.5217	0.0128
Log(Review Count)	-0.1828	0.833	***	< 0.001	0.0087
Log(Description Length)	0.5227	1.6866	***	< 0.001	0.0281
Name Length (Chars)	-0.0482	0.9529	***	< 0.001	0.0024
Has Website (Yes=1)	0.0963	1.1011	*	0.0331	0.0452
Log(Days Since Update)	0.1067	1.1126	***	< 0.001	0.011
Log(App Age)	0.7614	2.1412	***	< 0.001	0.028
Log(Size in MB)	-0.4052	0.6668	***	< 0.001	0.0182
Country: DE	-0.4842	0.6162	***	< 0.001	0.0554
Country: FR	-0.5137	0.5983	***	< 0.001	0.0561
Country: GB	-0.3617	0.6965	***	< 0.001	0.0534
Category: Business	0.0752	1.0781		0.7553	0.2413
Category: Developer Tools	1.4204	4.1388	***	< 0.001	0.3347
Category: Education	0.5286	1.6966	*	0.0178	0.223
Category: Entertainment	0.4059	1.5007	.	0.0719	0.2255
Category: Finance	0.0277	1.028		0.9117	0.2494
Category: Food & Drink	0.3071	1.3594		0.3338	0.3177
Category: Games	-0.1603	0.8519		0.4658	0.2198
Category: Graphics & Design	0.1271	1.1355		0.652	0.2819
Category: Health & Fitness	0.0413	1.0422		0.8576	0.2302
Category: Lifestyle	-0.4856	0.6153	*	0.0444	0.2416
Category: Magazines & Newspapers	-9.9611	0	***	< 0.001	1.00E-04
Category: Medical	-0.1216	0.8855		0.6435	0.2627
Category: Music	-0.2605	0.7706		0.3138	0.2586
Category: Navigation	0.2655	1.3041		0.257	0.2343

Continuation of Table 6

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: News	-0.3007	0.7403		0.2516	0.2623
Category: Photo & Video	0.4545	1.5754	*	0.0418	0.2233
Category: Productivity	0.1128	1.1194		0.6183	0.2264
Category: Reference	0.3972	1.4877		0.1007	0.242
Category: Shopping	-1.5835	0.2052	**	0.0038	0.5473
Category: Social Networking	0.1343	1.1437		0.5946	0.2523
Category: Sports	-0.3046	0.7375		0.2306	0.2541
Category: Stickers	5.4542	233.7439	***	< 0.001	0.4197
Category: Travel	0.1881	1.2069		0.4339	0.2403
Category: Utilities	0.0777	1.0808		0.7248	0.2207
Category: Weather	0.667	1.9484	**	0.0052	0.2389

Source: Compiled by the author based on Multinomial Logit regression analysis of the iOS dataset.

Table 7

MNL Parameter Estimates: ***Freemium*** *Strategy vs. Hybrid Baseline (iOS)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	1.2861	3.6188	***	< 0.001	0.1815
Average Rating (1-5)	-0.054	0.9474	***	< 0.001	0.0068
Log(Review Count)	-0.1873	0.8292	***	< 0.001	0.005
Log(Description Length)	-0.1619	0.8505	***	< 0.001	0.0137
Name Length (Chars)	-0.0325	0.968	***	< 0.001	0.0014
Has Website (Yes=1)	-0.6174	0.5393	***	< 0.001	0.0225
Log(Days Since Update)	0.0174	1.0176	**	0.0054	0.0063
Log(App Age)	0.0173	1.0175	.	0.0886	0.0102
Log(Size in MB)	0.0968	1.1016	***	< 0.001	0.0106
Country: DE	-0.6233	0.5362	***	< 0.001	0.0312
Country: FR	-0.6406	0.527	***	< 0.001	0.0316
Country: GB	-0.4448	0.6409	***	< 0.001	0.0298
Category: Business	0.9504	2.5868	***	< 0.001	0.1451
Category: Developer Tools	0.2748	1.3163		0.2853	0.2572
Category: Education	0.1098	1.116		0.4424	0.1429
Category: Entertainment	-0.0513	0.95		0.7227	0.1447
Category: Finance	0.7847	2.1917	***	< 0.001	0.1501
Category: Food & Drink	-0.0472	0.9539		0.8243	0.2126
Category: Games	-0.4698	0.6251	***	< 0.001	0.1401
Category: Graphics & Design	0.5274	1.6946	***	< 0.001	0.1545
Category: Health & Fitness	0.4162	1.5162	**	0.0037	0.1432
Category: Lifestyle	0.5077	1.6614	***	< 0.001	0.1436

Continuation of Table 7

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Magazines & Newspapers	-0.3419	0.7104		0.3605	0.3739
Category: Medical	0.8164	2.2624	***	< 0.001	0.1525
Category: Music	-0.4669	0.627	**	0.0048	0.1654
Category: Navigation	-0.0527	0.9487		0.7324	0.1541
Category: News	-0.6512	0.5214	***	< 0.001	0.1824
Category: Photo & Video	0.0442	1.0452		0.7581	0.1436
Category: Productivity	0.146	1.1572		0.3102	0.1439
Category: Reference	-0.0069	0.9931		0.9646	0.1557
Category: Shopping	0.5127	1.6699	**	0.0035	0.1759
Category: Social Networking	-0.0577	0.9439		0.7099	0.1551
Category: Sports	0.2896	1.3358	.	0.0571	0.1522
Category: Stickers	1.3713	3.9404	**	0.002	0.4433
Category: Travel	0.5599	1.7505	***	< 0.001	0.1486
Category: Utilities	-0.1218	0.8853		0.3863	0.1406
Category: Weather	-1.3963	0.2475	***	< 0.001	0.2027

Source: Compiled by the author based on Multinomial Logit regression analysis of the iOS dataset.

Table 8
Model Fit Specifications for iOS MNL Model

Metric	Value	Interpretation
Observations	94900	Sample Size
McFadden Pseudo R2	0.2164	0.2-0.4 is excellent
AIC	121726.74	Lower is better
BIC	123126.81	Lower is better

Source: Compiled by the author based on Multinomial Logit regression analysis of the iOS dataset.

Annex 3: Multinomial Logit Regression Results: Determinants of Pricing Strategy Selection (Android Ecosystem)

Table 9

MNL Parameter Estimates: ***Ad-Supported*** *Strategy vs. Hybrid Baseline (Android)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	2.5677	13.0364	***	< 0.001	0.2743
Average Rating (1-5)	-0.1262	0.8815	***	< 0.001	0.0164
Log(Review Count)	-0.1758	0.8388	***	< 0.001	0.0107
Log(Description Length)	-0.7308	0.4815	***	< 0.001	0.0251
Name Length (Chars)	-0.0102	0.9899	***	< 0.001	0.0017
Has_Website (Yes=1)	-0.2185	0.8037	***	< 0.001	0.0537
Log(Days Since Update)	0.1575	1.1705	***	< 0.001	0.0124
Log(App Age)	0.0947	1.0993	***	< 0.001	0.0228
Country: DE	-0.3899	0.6771	***	< 0.001	0.0495
Country: FR	-0.4517	0.6366	***	< 0.001	0.0508
Country: GB	-0.3697	0.6909	***	< 0.001	0.0491
Downloads: 100	10.4121	33261.1535	***	< 0.001	0.2465
Downloads: 500	1.6218	5.0621	**	0.0035	0.5552
Downloads: 1,000	1.245	3.4729	***	< 0.001	0.1955
Downloads: 5,000	0.853	2.3468	***	< 0.001	0.1614
Downloads: 10,000	1.3702	3.9361	***	< 0.001	0.0999
Downloads: 50,000	0.8681	2.3824	***	< 0.001	0.107
Downloads: 100,000	0.9185	2.5055	***	< 0.001	0.0843
Downloads: 500,000	0.8951	2.4477	***	< 0.001	0.0888
Downloads: 1,000,000+	0.9768	2.6559	***	< 0.001	0.078
Downloads: 5,000,000+	0.9837	2.6744	***	< 0.001	0.0867
Downloads: 10,000,000+	1.036	2.8179	***	< 0.001	0.0817
Downloads: 50,000,000+	1.1429	3.1358	***	< 0.001	0.1054
Downloads: 100,000,000+	1.4644	4.3251	***	< 0.001	0.1031
Downloads: 500,000,000+	2.123	8.3559	***	< 0.001	0.1832
Downloads: 1,000,000,000+	2.0012	7.3978	***	< 0.001	0.196
Downloads: 5,000,000,000+	2.2907	9.8822	***	< 0.001	0.5934
Downloads: 10,000,000,000+	4.1671	64.5274	***	< 0.001	0.5914
Category: Adventure	0.2223	1.249		0.284	0.2075
Category: Arcade	0.8828	2.4178	***	< 0.001	0.1691
Category: Art & Design	0.7505	2.1181	***	< 0.001	0.2199
Category: Auto & Vehicles	1.5067	4.5118	***	< 0.001	0.2781
Category: Beauty	1.1809	3.2574	***	< 0.001	0.2954
Category: Board	1.1896	3.2857	***	< 0.001	0.1628
Category: Books & Reference	2.0415	7.7021	***	< 0.001	0.1898

Continuation of Table 9

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Business	0.7561	2.1301	**	0.0035	0.2591
Category: Card	1.1863	3.2748	***	< 0.001	0.1666
Category: Casino	0.0758	1.0787		0.7826	0.2747
Category: Casual	0.7651	2.1491	***	< 0.001	0.1506
Category: Comics	1.034	2.8123	**	0.0011	0.3157
Category: Communication	2.2816	9.7927	***	< 0.001	0.1673
Category: Dating	-0.2549	0.775		0.6376	0.541
Category: Education	0.921	2.5117	***	< 0.001	0.1572
Category: Educational	0.32	1.3771		0.1081	0.1992
Category: Entertainment	1.7613	5.8197	***	< 0.001	0.1419
Category: Events	0.7861	2.1948		0.1567	0.5551
Category: Finance	3.0306	20.7104	***	< 0.001	0.1824
Category: Food & Drink	2.7328	15.3762	***	< 0.001	0.2486
Category: Health & Fitness	0.9789	2.6615	***	< 0.001	0.1623
Category: House & Home	3.1593	23.5547	***	< 0.001	0.2822
Category: Libraries & Demo	1.6249	5.0777	**	0.0011	0.4984
Category: Lifestyle	1.3816	3.9811	***	< 0.001	0.1618
Category: Maps & Navigation	1.7584	5.8033	***	< 0.001	0.1872
Category: Medical	1.7896	5.9868	***	< 0.001	0.2361
Category: Music	0.833	2.3002	**	0.0085	0.3164
Category: Music & Audio	1.1532	3.1684	***	< 0.001	0.1489
Category: News & Magazines	2.4724	11.8505	***	< 0.001	0.2011
Category: Parenting	2.0847	8.0418	***	< 0.001	0.272
Category: Personalization	1.9476	7.012	***	< 0.001	0.1538
Category: Photography	1.3311	3.7851	***	< 0.001	0.1622
Category: Productivity	0.8291	2.2912	***	< 0.001	0.1713
Category: Puzzle	0.5993	1.8209	***	< 0.001	0.1557
Category: Racing	0.2548	1.2902		0.184	0.1918
Category: Role Playing	0.4671	1.5954	*	0.0139	0.19
Category: Shopping	4.8862	132.4501	***	< 0.001	0.2438
Category: Simulation	0.5329	1.7039	***	< 0.001	0.143
Category: Social	1.2086	3.3489	***	< 0.001	0.2177
Category: Sports	0.5645	1.7586	***	< 0.001	0.1477
Category: Strategy	0.0909	1.0952		0.6988	0.235
Category: Tools	1.3612	3.901	***	< 0.001	0.1356
Category: Travel & Local	3.2239	25.1271	***	< 0.001	0.187
Category: Trivia	0.7449	2.1061	**	0.0038	0.2571
Category: Video Players & Editors	0.9572	2.6045	***	< 0.001	0.1774

Continuation of Table 9

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Weather	2.0348	7.6504	***	< 0.001	0.1916
Category: Word	0.415	1.5144	*	0.0376	0.1996

Source: Compiled by the author based on Multinomial Logit regression analysis of the Android dataset.

Table 10

*MNL Parameter Estimates: **Truly Free** Strategy vs. Hybrid Baseline (Android)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	15.2678	4272969.875	***	< 0.001	0.2764
Average Rating (1-5)	-0.2118	0.8092	***	< 0.001	0.0155
Log(Review Count)	-0.0149	0.9853		0.1286	0.0098
Log(Description Length)	-0.9977	0.3687	***	< 0.001	0.0245
Name Length (Chars)	-0.0195	0.9807	***	< 0.001	0.0016
Has_Website (Yes=1)	-0.8983	0.4072	***	< 0.001	0.0467
Log(Days Since Update)	-0.0317	0.9688	**	0.0076	0.0119
Log(App Age)	0.1586	1.1719	***	< 0.001	0.0223
Country: DE	-0.1906	0.8265	***	< 0.001	0.0471
Country: FR	-0.2019	0.8172	***	< 0.001	0.0483
Country: GB	-0.1588	0.8531	***	< 0.001	0.0466
Downloads: 100	1.0637	2.8969	***	< 0.001	0.256
Downloads: 500	-8.3405	2.00E-04	***	< 0.001	0.5651
Downloads: 1,000	-7.9627	3.00E-04	***	< 0.001	0.174
Downloads: 5,000	-9.0516	1.00E-04	***	< 0.001	0.1486
Downloads: 10,000	-8.5553	2.00E-04	***	< 0.001	0.0921
Downloads: 50,000	-8.837	1.00E-04	***	< 0.001	0.0948
Downloads: 100,000	-9.0466	1.00E-04	***	< 0.001	0.0752
Downloads: 500,000	-9.5897	1.00E-04	***	< 0.001	0.0811
Downloads: 1,000,000+	-9.7223	1.00E-04	***	< 0.001	0.0708
Downloads: 5,000,000+	-9.8129	1.00E-04	***	< 0.001	0.08
Downloads: 10,000,000+	-10.1971	0	***	< 0.001	0.0759
Downloads: 50,000,000+	-10.1662	0	***	< 0.001	0.1026
Downloads: 100,000,000+	-10.2446	0	***	< 0.001	0.1022
Downloads: 500,000,000+	-9.8384	1.00E-04	***	< 0.001	0.1862
Downloads: 1,000,000,000+	-8.675	2.00E-04	***	< 0.001	0.1545
Downloads: 5,000,000,000+	-8.1242	3.00E-04	***	< 0.001	0.3992
Downloads: 10,000,000,000+	-7.2511	7.00E-04	***	< 0.001	0.531
Category: Adventure	0.705	2.0239	***	< 0.001	0.2079
Category: Arcade	0.1867	1.2053		0.3879	0.2163

Continuation of Table 10

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Art & Design	1.4981	4.4733	***	< 0.001	0.2198
Category: Auto & Vehicles	3.6519	38.5489	***	< 0.001	0.2168
Category: Beauty	1.9262	6.8631	***	< 0.001	0.2842
Category: Board	0.4804	1.6167	*	0.0223	0.2103
Category: Books & Reference	2.909	18.3392	***	< 0.001	0.1906
Category: Business	4.1763	65.1275	***	< 0.001	0.1758
Category: Card	-1.6087	0.2002	***	< 0.001	0.4101
Category: Casino	-0.6118	0.5424		0.1057	0.3781
Category: Casual	-0.3214	0.7251		0.1085	0.2002
Category: Comics	0.3533	1.4238		0.4422	0.4597
Category: Communication	2.8685	17.6097	***	< 0.001	0.1784
Category: Dating	-21.0181	0	***	< 0.001	0
Category: Education	2.2832	9.8084	***	< 0.001	0.1611
Category: Educational	1.715	5.5564	***	< 0.001	0.1851
Category: Entertainment	1.9243	6.8502	***	< 0.001	0.1595
Category: Events	4.0747	58.8336	***	< 0.001	0.2809
Category: Finance	5.4506	232.8957	***	< 0.001	0.178
Category: Food & Drink	4.6413	103.6743	***	< 0.001	0.2252
Category: Health & Fitness	2.2569	9.5531	***	< 0.001	0.1623
Category: House & Home	3.6482	38.4049	***	< 0.001	0.2821
Category: Libraries & Demo	1.9623	7.116	***	< 0.001	0.4764
Category: Lifestyle	2.6158	13.6778	***	< 0.001	0.164
Category: Maps & Navigation	3.286	26.7357	***	< 0.001	0.1787
Category: Medical	3.5896	36.2201	***	< 0.001	0.2041
Category: Music	0.1581	1.1712		0.7699	0.5403
Category: Music & Audio	1.5112	4.5323	***	< 0.001	0.1657
Category: News & Magazines	1.9025	6.7026	***	< 0.001	0.2352
Category: Parenting	2.7009	14.8927	***	< 0.001	0.2713
Category: Personalization	1.3212	3.7477	***	< 0.001	0.1917
Category: Photography	1.2926	3.6422	***	< 0.001	0.1915
Category: Productivity	2.7086	15.008	***	< 0.001	0.1605
Category: Puzzle	-0.5564	0.5733	**	0.009	0.213
Category: Racing	-1.4071	0.2449	***	< 0.001	0.3701
Category: Role Playing	-0.7927	0.4526	**	0.0076	0.2967
Category: Shopping	6.3166	553.6703	***	< 0.001	0.2476
Category: Simulation	-0.8662	0.4206	***	< 0.001	0.2
Category: Social	1.9938	7.3436	***	< 0.001	0.2068

Continuation of Table 10

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Sports	0.4407	1.5537	**	0.0093	0.1695
Category: Strategy	-0.5568	0.573	.	0.0906	0.329
Category: Tools	1.9828	7.263	***	< 0.001	0.152
Category: Travel & Local	5.1141	166.3454	***	< 0.001	0.1864
Category: Trivia	-0.6335	0.5307		0.1516	0.4418
Category: Video Players & Editors	1.6678	5.3004	***	< 0.001	0.1842
Category: Weather	1.3367	3.8064	***	< 0.001	0.2396
Category: Word	-0.2813	0.7548		0.2877	0.2646

Source: Compiled by the author based on Multinomial Logit regression analysis of the Android dataset.

Table 11

MNL Parameter Estimates: ***Paid*** *Strategy vs. Hybrid Baseline (Android)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	-21.4671	0	***	< 0.001	0.5487
Average Rating (1-5)	-0.0054	0.9946		0.8598	0.0305
Log(Review Count)	0.7465	2.1096	***	< 0.001	0.0248
Log(Description Length)	0.2308	1.2595	***	< 0.001	0.0529
Name Length (Chars)	0.0026	1.0026		0.4061	0.0032
Has_Website (Yes=1)	-0.3051	0.7371	**	0.0014	0.0956
Log(Days Since Update)	0.0415	1.0424	.	0.0564	0.0218
Log(App Age)	1.3763	3.9601	***	< 0.001	0.0488
Country: DE	1.2059	3.3398	***	< 0.001	0.0918
Country: FR	1.5448	4.6868	***	< 0.001	0.0953
Country: GB	1.2093	3.3511	***	< 0.001	0.092
Downloads: 100	21.7526	2799119576	***	< 0.001	0.2651
Downloads: 500	14.4992	1981196.501	***	< 0.001	0.4988
Downloads: 1,000	11.9755	158812.726	***	< 0.001	0.1886
Downloads: 5,000	10.349	31225.103	***	< 0.001	0.1706
Downloads: 10,000	9.1829	9729.3408	***	< 0.001	0.1207
Downloads: 50,000	7.4107	1653.5879	***	< 0.001	0.1277
Downloads: 100,000	5.9649	389.4985	***	< 0.001	0.1106
Downloads: 500,000	3.9383	51.3306	***	< 0.001	0.1358
Downloads: 1,000,000+	1.6858	5.397	***	< 0.001	0.1449
Downloads: 5,000,000+	0.1356	1.1453		0.4932	0.198
Downloads: 10,000,000+	-3.3799	0.0341	***	< 0.001	0.3647

Continuation of Table 11

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Downloads: 50,000,000+	-3.8643	0.021	***	< 0.001	0.4993
Downloads: 100,000,000+	-18.5258	0	***	< 0.001	0
Downloads: 500,000,000+	-9.4953	1.00E-04	***	< 0.001	0.001
Downloads: 1,000,000,000+	-13.9147	0	***	< 0.001	0
Downloads: 5,000,000,000+	-10.3099	0	***	< 0.001	0
Downloads: 10,000,000,000+	-13.964	0	***	< 0.001	0
Category: Adventure	-1.2146	0.2968	***	< 0.001	0.2276
Category: Arcade	-0.2339	0.7915		0.3421	0.2462
Category: Art & Design	-0.7612	0.4671	*	0.0279	0.3462
Category: Auto & Vehicles	-3.6049	0.0272	***	< 0.001	0.57
Category: Beauty	-2.3418	0.0962	***	< 0.001	0.5742
Category: Board	-1.2803	0.278	***	< 0.001	0.2174
Category: Books & Reference	-0.887	0.4119	**	0.001	0.2703
Category: Business	-3.7894	0.0226	***	< 0.001	0.5447
Category: Card	-2.622	0.0727	***	< 0.001	0.2553
Category: Casino	-4.0227	0.0179	***	< 0.001	0.5859
Category: Casual	-2.1547	0.1159	***	< 0.001	0.2623
Category: Comics	-4.4247	0.012	***	< 0.001	1.0786
Category: Communication	-1.3181	0.2676	***	< 0.001	0.3234
Category: Dating	-15.8288	0	***	< 0.001	0
Category: Education	-2.0605	0.1274	***	< 0.001	0.2099
Category: Educational	-1.9907	0.1366	***	< 0.001	0.34
Category: Entertainment	-2.9399	0.0529	***	< 0.001	0.2379
Category: Events	-1.906	0.1487	**	0.003	0.6415
Category: Finance	-1.9018	0.1493	***	< 0.001	0.3109
Category: Food & Drink	-2.4499	0.0863	***	< 0.001	0.5643
Category: Health & Fitness	-3.9786	0.0187	***	< 0.001	0.2931
Category: House & Home	-17.3898	0	***	< 0.001	0
Category: Libraries & Demo	-11.9895	0	***	< 0.001	0
Category: Lifestyle	-3.2935	0.0371	***	< 0.001	0.2593
Category: Maps & Navigation	-2.0466	0.1292	***	< 0.001	0.2795
Category: Medical	-2.4598	0.0854	***	< 0.001	0.3311
Category: Music	-12.9997	0	***	< 0.001	0
Category: Music & Audio	-1.9188	0.1468	***	< 0.001	0.2099
Category: News & Magazines	-20.4322	0	***	< 0.001	0
Category: Parenting	-18.7764	0	***	< 0.001	0
Category: Personalization	0.4056	1.5002	*	0.0486	0.2056
Category: Photography	-1.2314	0.2919	***	< 0.001	0.266

Continuation of Table 11

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Productivity	-2.115	0.1206	***	< 0.001	0.2428
Category: Puzzle	-2.2329	0.1072	***	< 0.001	0.2151
Category: Racing	-0.3871	0.679		0.13	0.2557
Category: Role Playing	-1.1002	0.3328	***	< 0.001	0.2192
Category: Shopping	-17.0116	0	***	< 0.001	0
Category: Simulation	-0.7689	0.4635	***	< 0.001	0.1782
Category: Social	-17.9157	0	***	< 0.001	0
Category: Sports	-2.8564	0.0575	***	< 0.001	0.2318
Category: Strategy	-0.2805	0.7554		0.1854	0.2118
Category: Tools	-1.3824	0.251	***	< 0.001	0.1784
Category: Travel & Local	-2.1526	0.1162	***	< 0.001	0.431
Category: Trivia	-2.6915	0.0678	***	< 0.001	0.4703
Category: Video Players & Editors	-1.1928	0.3034	***	< 0.001	0.3034
Category: Weather	-1.3566	0.2575	***	< 0.001	0.3075
Category: Word	-3.0074	0.0494	***	< 0.001	0.3241

Source: Compiled by the author based on Multinomial Logit regression analysis of the Android dataset.

Table 12

MNL Parameter Estimates: ***Freemium*** *Strategy vs. Hybrid Baseline (Android)*

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Intercept	-0.3521	0.7032		0.1323	0.2339
Average Rating (1-5)	-0.157	0.8547	***	< 0.001	0.0146
Log(Review Count)	0.1389	1.149	***	< 0.001	0.009
Log(Description Length)	-0.0888	0.915	***	< 0.001	0.0244
Name Length (Chars)	-0.0027	0.9973	*	0.0447	0.0013
Has_Website (Yes=1)	-0.287	0.7505	***	< 0.001	0.0454
Log(Days Since Update)	-0.0874	0.9163	***	< 0.001	0.0102
Log(App Age)	-0.0959	0.9086	***	< 0.001	0.0177
Country: DE	0.2055	1.2282	***	< 0.001	0.0403
Country: FR	0.2414	1.273	***	< 0.001	0.0414
Country: GB	0.2045	1.227	***	< 0.001	0.0401
Downloads: 100	10.8577	51932.9618	***	< 0.001	0.3943
Downloads: 500	2.2704	9.6836	***	< 0.001	0.6215
Downloads: 1,000	3.3282	27.8867	***	< 0.001	0.169
Downloads: 5,000	2.7269	15.285	***	< 0.001	0.1372

Continuation of Table 12

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Downloads: 10,000	2.6586	14.277	***	< 0.001	0.0928
Downloads: 50,000	2.2889	9.8642	***	< 0.001	0.0934
Downloads: 100,000	2.0782	7.9903	***	< 0.001	0.0779
Downloads: 500,000	1.5364	4.648	***	< 0.001	0.0808
Downloads: 1,000,000+	1.2462	3.4771	***	< 0.001	0.0736
Downloads: 5,000,000+	0.775	2.1707	***	< 0.001	0.0798
Downloads: 10,000,000+	0.395	1.4843	***	< 0.001	0.0771
Downloads: 50,000,000+	0.0438	1.0448		0.6502	0.0965
Downloads: 100,000,000+	-0.4096	0.6639	***	< 0.001	0.1042
Downloads: 500,000,000+	0.4852	1.6245	**	0.0026	0.1609
Downloads: 1,000,000,000+	0.3844	1.4687	*	0.037	0.1843
Downloads: 5,000,000,000+	0.7571	2.1321		0.1196	0.4865
Downloads: 10,000,000,000+	2.005	7.4262	***	< 0.001	0.5545
Category: Adventure	-0.0056	0.9944		0.9605	0.1127
Category: Arcade	-1.0737	0.3417	***	< 0.001	0.1652
Category: Art & Design	0.7922	2.2082	***	< 0.001	0.1196
Category: Auto & Vehicles	0.9699	2.6377	***	< 0.001	0.1876
Category: Beauty	-0.8303	0.4359	*	0.0122	0.3314
Category: Board	-0.2783	0.7571	*	0.0182	0.1179
Category: Books & Reference	1.0341	2.8126	***	< 0.001	0.1361
Category: Business	1.0622	2.8927	***	< 0.001	0.1338
Category: Card	-0.7849	0.4562	***	< 0.001	0.1253
Category: Casino	-0.6832	0.505	***	< 0.001	0.162
Category: Casual	-0.8416	0.431	***	< 0.001	0.1106
Category: Comics	1.056	2.8749	***	< 0.001	0.1867
Category: Communication	0.5062	1.659	***	< 0.001	0.1354
Category: Dating	1.0251	2.7875	***	< 0.001	0.1766
Category: Education	0.9242	2.5198	***	< 0.001	0.0904
Category: Educational	0.9014	2.4631	***	< 0.001	0.1073
Category: Entertainment	0.2658	1.3045	**	0.0041	0.0927
Category: Events	-0.1738	0.8405		0.6573	0.3917
Category: Finance	1.2234	3.3986	***	< 0.001	0.1425
Category: Food & Drink	2.1284	8.401	***	< 0.001	0.191
Category: Health & Fitness	1.1954	3.305	***	< 0.001	0.0879
Category: House & Home	1.7045	5.4985	***	< 0.001	0.247
Category: Libraries & Demo	-10.825	0	***	< 0.001	0

Continuation of Table 12

Variable	Coefficient	Odds Ratio	Significance	P Value	Std Error
Category: Lifestyle	0.4212	1.5238	***	< 0.001	0.101
Category: Maps & Navigation	0.9051	2.4723	***	< 0.001	0.1302
Category: Medical	1.1298	3.095	***	< 0.001	0.1675
Category: Music	-0.0643	0.9377		0.8104	0.2678
Category: Music & Audio	-0.2359	0.7898	*	0.0177	0.0994
Category: News & Magazines	1.2293	3.4189	***	< 0.001	0.1582
Category: Parenting	1.2802	3.5974	***	< 0.001	0.1772
Category: Personalization	-0.1275	0.8803		0.3142	0.1267
Category: Photography	0.3943	1.4833	***	< 0.001	0.1092
Category: Productivity	1.1767	3.2437	***	< 0.001	0.0909
Category: Puzzle	-1.1505	0.3165	***	< 0.001	0.1098
Category: Racing	-0.6415	0.5265	***	< 0.001	0.1396
Category: Role Playing	0.3928	1.4811	***	< 0.001	0.1007
Category: Shopping	1.0854	2.9606	***	< 0.001	0.2802
Category: Simulation	-1.0557	0.3479	***	< 0.001	0.0949
Category: Social	0.9154	2.4977	***	< 0.001	0.1365
Category: Sports	-0.5037	0.6043	***	< 0.001	0.0947
Category: Strategy	0.4753	1.6086	***	< 0.001	0.1054
Category: Tools	0.064	1.0661		0.4408	0.083
Category: Travel & Local	1.2716	3.5664	***	< 0.001	0.1592
Category: Trivia	-1.898	0.1499	***	< 0.001	0.3405
Category: Video Players & Editors	0.0398	1.0406		0.7435	0.1215
Category: Weather	-0.6183	0.5389	**	0.0021	0.2013
Category: Word	-2.0778	0.1252	***	< 0.001	0.2244

Source: Compiled by the author based on Multinomial Logit regression analysis of the Android dataset.

Table 13
Model Fit Specifications for Android MNL Model

Metric	**Value**	**Interpretation**
Observations	47096	Sample Size
McFadden Pseudo R2	0.2524	0.2-0.4 is excellent
AIC	98372.34	Lower is better
BIC	101000.32	Lower is better

Source: Compiled by the author based on Multinomial Logit regression analysis of the Android dataset.

Annex 5: Ordinary Least Squares Regression Results: Impact of Monetization Strategy on Rating Volume (iOS Ecosystem)

Table 14

OLS Regression Coefficients: The Impact of Monetization Strategy on Log User Rating Volume (iOS)

Variable	Coefficient	Std Error	p value	t value	Significance
Intercept	-5.37	0.139	0	-38.517	***
Strategy: Paid	-0.851	0.04	0	-21.212	***
Strategy: Freemium	-0.838	0.022	0	-37.308	***
Strategy: Ad_Supported	-0.069	0.051	0.179	-1.345	
Strategy: Truly_Free	-0.895	0.039	0	-22.698	***
Average Rating (1-5)	0.687	0.005	0	135.057	***
Log(Description Length)	0.317	0.01	0	30.959	***
Log (Name Length)	-0.045	0.02	0.023	-2.27	**
Log(App Age)	0.859	0.007	0	119.238	***
Log(Days Since Update)	-0.368	0.004	0	-89.441	***
Log(Size in MB)	0.491	0.008	0	64.375	***
Country: DE	-2.204	0.021	0	-106.37	***
Country: FR	-2.262	0.021	0	-108.736	***
Country: GB	-1.704	0.02	0	-84.057	***
Category: Business	-0.241	0.103	0.019	-2.342	**
Category: Developer Tools	0.036	0.198	0.857	0.181	
Category: Education	-0.409	0.1	0	-4.103	***
Category: Entertainment	0.303	0.1	0.003	3.018	***
Category: Finance	-0.233	0.105	0.026	-2.226	**
Category: Food & Drink	0.133	0.128	0.3	1.037	
Category: Games	0.652	0.096	0	6.763	***
Category: Graphics & Design	0.301	0.111	0.007	2.702	***
Category: Health & Fitness	-0.055	0.1	0.585	-0.546	
Category: Lifestyle	-0.182	0.101	0.071	-1.806	*
Category: Magazines & Newspapers	-1.101	0.248	0	-4.443	***
Category: Medical	-0.743	0.111	0	-6.706	***
Category: Music	0.562	0.109	0	5.157	***
Category: Navigation	-0.502	0.107	0	-4.699	***
Category: News	-0.498	0.119	0	-4.198	***
Category: Photo & Video	0.209	0.1	0.036	2.096	**

Continuation of Table 14

Variable	Coefficient	Std Error	p value	t value	Significance
Category: Productivity	0.232	0.1	0.02	2.318	**
Category: Reference	-0.178	0.11	0.105	-1.619	
Category: Shopping	0.489	0.112	0	4.357	***
Category: Social Networking	0.196	0.108	0.07	1.813	*
Category: Sports	-0.814	0.109	0	-7.492	***
Category: Stickers	0.56	0.216	0.009	2.595	***
Category: Travel	-0.464	0.104	0	-4.475	***
Category: Utilities	0.187	0.097	0.055	1.919	*
Category: Weather	-0.083	0.115	0.474	-0.717	

Source**:** Compiled by the author based on Ordinary Least Squares regression analysis of the iOS dataset.

Table 15

Summary of Model Fit and Diagnostic Tests for OLS Regression (iOS)

Metric	Value
VIF_Strategy	1.639
VIF_Rating	1.441
VIF_log_desc_length	1.361
VIF_log_name_length	1.135
VIF_log_age	1.287
VIF_log_days_since_update	1.374
VIF_Country	1.076
VIF_Category	2.263
VIF_log_size_mb	1.744
BP_Statistic	7238.37
BP_p_value	0
R_squared	0.605
Adj_R_squared	0.605
F_statistic	3818.852
Observations	94900

Source**:** Compiled by the author based on Ordinary Least Squares regression analysis of the Android dataset.

Annex 7: Ordinary Least Squares Regression Results: Impact of Monetization Strategy on Rating Volume (Android Ecosystem)

Table 16

OLS Regression Coefficients: The Impact of Monetization Strategy on User Rating Volume (Android)

Variable	Coefficient	Std Error	t value	p value	Significance
Intercept	6.765	0.152	44.557	0	***
Strategy: Paid	0.874	0.04	21.797	0	***
Strategy: Freemium	0.192	0.02	9.477	0	***
Strategy: Ad_Supported	-0.349	0.025	-13.963	0	***
Strategy: Truly_Free	-0.586	0.024	-24.608	0	***
Average Rating (1-5)	1.331	0.007	199.423	0	***
Log(Description Length)	0.102	0.012	8.888	0	***
Log (Name Length)	0.176	0.01	17.07	0	***
Log(App Age)	0.28	0.009	29.457	0	***
Log(Days Since Update)	-0.048	0.005	-8.718	0	***
Country: DE	-0.148	0.02	-7.342	0	***
Country: FR	-0.265	0.02	-13.072	0	***
Country: GB	-0.113	0.02	-5.649	0	***
Category: Adventure	0.037	0.068	0.544	0.586	
Category: Arcade	-0.25	0.07	-3.57	0	***
Category: Art & Design	-0.39	0.077	-5.083	0	***
Category: Auto & Vehicles	-0.753	0.093	-8.087	0	***
Category: Beauty	-0.646	0.138	-4.701	0	***
Category: Board	-0.327	0.065	-5.056	0	***
Category: Books & Reference	-0.348	0.076	-4.612	0	***
Category: Business	-0.591	0.067	-8.793	0	***
Category: Card	0.053	0.067	0.792	0.429	
Category: Casino	0.318	0.09	3.538	0	***
Category: Casual	-0.424	0.058	-7.352	0	***
Category: Comics	-0.323	0.125	-2.593	0.01	***
Category: Communication	-0.24	0.07	-3.427	0.001	***
Category: Dating	0.471	0.125	3.76	0	***
Category: Education	-0.714	0.054	-13.294	0	***
Category: Educational	-1.41	0.066	-21.4	0	***
Category: Entertainment	-0.519	0.053	-9.791	0	***

Continuation of Table 16

Variable	Coefficient	Std Error	p value	t value	Significance
Category: Events	-0.631	0.148	-4.269	0	***
Category: Finance	-0.676	0.06	-11.299	0	***
Category: Food & Drink	-0.653	0.083	-7.833	0	***
Category: Health & Fitness	-0.464	0.053	-8.679	0	***
Category: House & Home	-0.734	0.122	-6.011	0	***
Category: Libraries & Demo	0.322	0.276	1.164	0.244	
Category: Lifestyle	-0.329	0.059	-5.624	0	***
Category: Maps & Navigation	-0.525	0.07	-7.479	0	***
Category: Medical	-1.263	0.083	-15.198	0	***
Category: Music	-0.899	0.146	-6.168	0	***
Category: Music & Audio	-0.529	0.055	-9.635	0	***
Category: News & Magazines	-0.284	0.09	-3.146	0.002	***
Category: Parenting	-0.406	0.113	-3.59	0	***
Category: Personalization	-0.475	0.064	-7.37	0	***
Category: Photography	-0.189	0.064	-2.954	0.003	***
Category: Productivity	-0.278	0.055	-5.087	0	***
Category: Puzzle	-0.17	0.057	-3.003	0.003	***
Category: Racing	-0.285	0.071	-3.987	0	***
Category: Role Playing	0.383	0.064	6.027	0	***
Category: Shopping	-0.86	0.067	-12.89	0	***
Category: Simulation	-0.164	0.05	-3.269	0.001	***
Category: Social	0.044	0.085	0.525	0.6	
Category: Sports	-0.235	0.053	-4.401	0	***
Category: Strategy	0.22	0.067	3.278	0.001	***
Category: Tools	-0.29	0.047	-6.133	0	***
Category: Travel & Local	-0.461	0.065	-7.041	0	***
Category: Trivia	0.048	0.114	0.419	0.675	
Category: Video Players & Editors	-0.255	0.068	-3.729	0	***
Category: Weather	-0.159	0.091	-1.744	0.081	*
Category: Word	-0.062	0.079	-0.782	0.434	
Installs: 1+	-4.264	0.287	-14.865	0	***
Installs: 100+	-9.743	0.22	-44.351	0	***
Installs: 500+	-10.777	0.195	-55.321	0	***
Installs: 1,000+	-10.625	0.106	-100.415	0	***

Continuation of Table 16

Variable	Coefficient	Std Error	p value	t value	Significance
Installs: 5,000+	-10.045	0.104	-96.832	0	***
Installs: 10,000+	-9.267	0.09	-102.967	0	***
Installs: 50,000+	-8.595	0.091	-94.395	0	***
Installs: 100,000+	-7.476	0.086	-86.715	0	***
Installs: 500,000+	-6.441	0.087	-73.771	0	***
Installs: 1,000,000+	-5.315	0.085	-62.608	0	***
Installs: 5,000,000+	-4.212	0.086	-48.745	0	***
Installs: 10,000,000+	-3.089	0.085	-36.333	0	***
Installs: 50,000,000+	-2.025	0.09	-22.605	0	***
Installs: 100,000,000+	-1.007	0.089	-11.265	0	***
Installs: 500,000,000+	0.23	0.117	1.976	0.048	**
Installs: 1,000,000,000+	-15.307	0.638	-24.002	0	***
Installs: 5,000,000,000+	0.982	0.238	4.13	0	***
Installs: 10,000,000,000+	1.916	0.238	8.042	0	***

Source**:** Compiled by the author based on Ordinary Least Squares regression analysis of the Android dataset.

Table 17

Summary of Model Fit and Diagnostic Tests for OLS Regression (Android)

Metric	Value
VIF_Strategy	2.146
VIF_Rating	1.3
VIF_log_desc_length	1.204
VIF_log_name_length	1.111
VIF_log_age	1.492
VIF_log_days_since_update	1.239
VIF_Country	1.035
VIF_Category	2.414
VIF_Installs_Factor	2.421
R_squared	0.844
Adj_R_squared	0.844
F_statistic	3304.825
Observations	47102

Source**:** Compiled by the author based on Ordinary Least Squares regression analysis of the Android dataset.