W.W. Biesbroeck

User Responses to Increased Value Capture in a Dominant Platform Ecosystem

User Responses to Increased Value Capture in a Dominant Platform Ecosystem

By

W.W. Biesbroeck

4588878

30-01-2025

in partial fulfilment of the requirements for the degree of

Master of Science

in Management of Technology

at the Delft University of Technology

.

Supervisor:	Dr. ir. V.C.M Sobota
Thesis committee:	Dr. G. van de Kaa
	E. Çelik

TU Delft

Executive summary

This thesis investigates the impact of increased value capture by a dominant platform sponsor on user behavior and ecosystem stability, focusing on YouTube in a single case experiment. Dominant platform ecosystems, such as YouTube, have come under increasing scrutiny for implementing value capture strategies that prioritize short term profits at the expense of long term ecosystem stability. These strategies often leverage high user lock-in created by network effects and switching costs, leaving users with few alternatives. The policy challenge lies in identifying how dominant sponsors can balance their value capture ambitions with the need to sustain user engagement and ecosystem health.

This thesis addresses the gap in understanding how users respond to value capture strategies, particularly ad load increase, in ecosystems where dominant platforms hold significant market power. The client for this research is the broader academic and policy makers of platform governance and sustainable ecosystem strategies. The central research question is: *How do users respond to increased value capture by the platform sponsor in a dominant platform ecosystem?*

Through the experiment, which investigated the impact of ad load increase on user disengagement from YouTube and willingness to pay for YouTube Premium (which provides an ad-free experience), the research demonstrated the following:

- Increasing ad load significantly raises user disengagement, characterized by reduced platform use or complete abandonment.

- The availability of a premium subscription mitigates this effect by providing a buyout option for dissatisfied users. However, participants that were more willing to pay for premium in the experimental scenario exhibited aversion to ads independent of increased ad load. This stabilization effect highlights the importance of offering tailored premium subscriptions that can appeal to specific user segments rather than simply serving as a buyout option from ads, thereby improving retention of users more effectively.

To address the tension between value capture and ecosystem sustainability, the following recommendations are proposed:

1. **Adopt a balanced value capture approach**: Sponsors should incrementally implement value capture strategies that don't exceed user tolerance levels and avoid destabilizing the ecosystem. Preferably, a sponsor should aim to reinvest captured value into user-focused improvements, such as increasing complement quality or enhanced features, to increase ecosystem sustainability.

2. **Enhance premium offerings**: Sponsors should develop premium options that appeal to certain groups of users rather than simply using them as a buyout option of increased value capture.

3. **Increase transparency and improve regulation**: Policy makers should incentivize transparency in monetization strategies or set limits to value capture to protect users. Clearly communicating the mechanisms of value capture strategies could help foster user trust and reduce perceived exploitation.

These recommendations advocate for a proactive and user-centric approach that balances monetization with long term platform ecosystem health. The theoretical framework presented in this thesis, including the conceptual model, can serve as a basis for future research in this field of platform research.

Implementing these recommendations would enable dominant platforms like YouTube to sustain their ecosystems and ensure user welfare while achieving their financial goals. For policymakers, this work underscores the importance of regulating platform governance to ensure sustainable and equitable value distribution. Aligning sponsor strategies with user expectations can mitigate the risks of ecosystem collapse and foster healthier platform dynamics. A collaborative approach involving sponsors, users, and policymakers is essential to achieve this balance.

Acknowledgements

I would like to express my gratitude to my supervisor Vladimir Sobota, for his guidance and support in many meetings. I want to thank him for his effort and encouragement throughout the thesis process. I would also like to thank the other thesis committee members, Geerten van de Kaa en Elif Çelik, for their expertise and constructive feedback, which helped me enhance the quality and direction of this research.

A special thanks to Leo Richards, for generously allowing me to use a video from his YouTube channel Natural World Facts for my experiment. Your contribution to the experiment is greatly appreciated. I also want to thank my brother, Ward Biesbroeck, for assisting me in editing the videos for the experiment. Thanks for your patience in helping me, you have saved me a lot of valuable time.

Table of contents

List of tables and figures

1. Introduction

Since the dawn of the digital age, online platforms have become increasingly relevant. Functioning as a virtual interaction medium, they have reshaped connection between businesses and customers, information sharing, and social interaction (Parker et al., 2016; Gawer & Cusumano, 2002). Some of the largest companies today, such as Meta, Amazon, and YouTube, have leveraged the platform business model with great success, granting them substantial dominance over their respective market. But this increase in dominance comes with great power. And with great power, comes great responsibility.

Large platforms have increasingly come under scrutiny over this topic, as they ever more often get accused of irresponsibly exploiting their great power (Rietveld & Schilling, 2020). For example, back in 2018, Facebook was entangled in the Cambridge-Analytica data scandal, where data from up to 87 million Facebook users was harvested and sold to parties aiming to influence the US elections and Brexit referendum (Confessore, 2018). In 2017, Google was fined €2.42 billion for breaching EU antitrust rules by abusing their dominance as a search engine (European Commission, 2017). Google was able to gain an unfair advantage through illegally promoting its own comparison shopping service in its search results, while demoting those of competitors. These are just two examples that were actually put to court, which leaves you wondering what other practices are left undiscovered. Many more examples of dominant platforms using their power to further their own interests have been discussed in journalistic articles (Doctorow, 2024). Recently, platform research has started to take more notice of this topic (Gawer, 2021; Rietveld & Schilling, 2020).

This thesis aims to further this relatively new field in platform research by building upon established literature to create a theoretical framework that can help analyze the ecosystems of such platforms. This process starts by understanding the core concepts and mechanisms that make up a platform ecosystem. Platform ecosystems are defined as complex networks of interdependent members, complementary products or services, and third-party stakeholders that interact to co-create value (Moore, 1993; Gawer & Cusumano, 2002). While research in this field has only taken shape a couple decades ago, the rise of the internet has played a catalyzing role in growing its importance (Parker et al., 2016). Platform ecosystems consist of four key groups: the platform sponsor, the provider, the complementors, and the users. The sponsor, also called the platform owner, is described as the party that owns the platforms' intellectual property. It hosts the ecosystem and is able to orchestrate its governance. The providers serve as the interface, such as mobile phones being providers for an app store. Although important to the ecosystem, this party is discussed less in this thesis. Complementors are the participants on the platform that provide offerings, while the users consume these offerings (Alstyne et al., 2016). The effect of value capture strategies on complementors in dominant platform ecosystem has already received moderate attention in scientific research (e.g. Zhu & Liu, 2018; Zhu, 2018; Rietveld et al., 2020; Lan et al, 2019), which makes it ever more interesting to do the same for users.

The ecosystem members each have their own motivations to take part on the platform. To create an incentive to stay involved, a platform must have value for each of the participants. The concept of value for platforms can be more abstract than in a regular value-chain model. In the context of platform ecosystems, value creation can be described as the collaborative interactions and processes through which sponsors, providers, complementors, and users collectively generate utility and benefits for some or all participants in the ecosystem. Therefore, the focus of a platform is to create value for the entire ecosystem, as this feeds back to all participants. Value capture, on the other hand, refers to the mechanisms by which individuals in the ecosystem monetize these interactions to achieve competitive advantages and secure financial returns (Ritala et al., 2013; Parker et al., 2016). Through its central position in the ecosystem, the sponsor often has the ability to orchestrate how value is created and captured on the platform. To increase the value of the ecosystem, the sponsor must decide how it can attract high quality complements to its platform and how it will reward their participation through value capture (Rietveld et al., 2019). In doing so, a balance is created where specific ecosystem members, including sponsors themselves, are able to capture value to make their participation worthwhile, while trying to avoid depletion of value for users. If value is taken disproportionately and users feel like their needs are not being met on the platform anymore, they might go looking for a platform that does (Alstyne et al., 2023).

But what if there are no other options? What if the platform is so dominant in its market that users can only decide to leave and miss out on the service entirely, or accept the negative effects of the sponsor's governance strategies? This is where the scope of this thesis begins. Research on this topic has focussed mainly on exploring different dominant sponsor strategies and the impact of implementation on complementors (Zhu, 2018; Zhu & Liu, 2018; Rietveld et al., 2020), while also explaining how pushing a platform ecosystem to its limits will ultimately lead to its collapse (Gawer, 2021; Knudsen & Belik, 2023; Duan & Li, 2023). Journalistic articles, such as those written by Cory Doctorow, have gone some steps further by analyzing the evolution of value capture of sponsors growing more dominant over time. Doctorow illustrated this evolution with the term 'enshittification,' where initial strategies aim to foster a nurturing ecosystem for users and complementors to create value, but switch to maximizing value capture once these parties become sufficiently locked in (Doctorow, 2024). This process towards maximizing value capture and the direct effect it has on users specifically, combined with how users respond in these situations, remain underexplored in platform research. Recent literature has focussed on how certain value capture strategies by dominant sponsors can negatively impact users' economic surplus and welfare (Anderson & Bedre Defolie, 2024) and what drives users to eventually disengage from a platform (Alstyne et al., 2023). Some studies have even started to investigate how these dominant platforms should be regulated (Li & Wang, 2021; Gutierrez, 2021) and what happens to a dominant platform ecosystem when policymakers step in through antitrust intervention (Thatchenkery & Katila, 2023; Katz, 2019). However, there is still a critical gap in collecting and analyzing the responses of users and understanding how the effects of increased value capture can ripple through the complex network of platform ecosystems. Rigorous empirical research in real world settings which causally connects increasing value capture to user behavior is underrepresented in platform research, which results in a missing insight into how dominant sponsors balance maximizing value capture with the stability of the ecosystem. Therefore, the research question for this thesis is:

How do users respond to increased value capture by the platform sponsor in a dominant platform ecosystem?

Without looking deeper into the direct effects of value capture strategies on users in dominant platform ecosystems, our theoretical understanding of platform dynamics remains incomplete. Over time, this can lead to incomplete knowledge for policymakers and possibly exploitive outcomes caused by a lack of necessary tools to analyze the needs of all members of these ecosystems. To address the research gap, this thesis proposes to deductively develop a theoretical framework with a conceptual model using the current theoretical knowledge on this topic. This framework will then be quantitatively tested using a single paradigmatic case experiment on the value capture strategy of increased ad load for the platform YouTube. The findings from the experiment empirically validate the conceptual model for this particular case and provide insights that may also be applied to similar cases involving increased value capture in other dominant platform ecosystems. Although underutilized in strategic management, choosing experimentation as the method of research can help bridge theory to practice in this field by enabling a higher degree of control and precision in identifying causal links (Bolinger et al., 2022). However, the experiment is not intended to serve as conclusive evidence for the theoretical framework created in this thesis as a whole, but rather as a step toward demonstrating its utility. The literature review and the experiment aim to find an answer to the research question and the following sub questions:

1) What strategies do dominant sponsors use to capture value, which directly impact users?
2) How do these strategies affect the platform ecosystem, specifically users?
3) How does the introduction of a premium option influence the response of users to increased value capture?

2. Literature review

The literature review is structured in a chronological order. It starts with the aspects of early platform research that are important for this thesis. The early research on platform ecosystems has laid the groundwork on which recent studies build their theories, helping to better understand other parts of the literature review. Then, more recent literature within the scope of the thesis is discussed regarding value capture by dominant sponsors. Platform sponsors employ a wide range of strategies to capture value, oftentimes indirectly affecting users. However, this thesis focuses on value capture strategies that can be readily implemented by dominant sponsors specifically and have a direct impact on users. The literature review then builds towards the conceptual model and hypotheses from there. Its purpose is to create a theoretical framework and the conceptual model, which is empirically tested in the experiment.

2.1 Early platform research

Early research on platforms introduced important mechanisms that still play vital roles within platform ecosystems today. Two terms from early platform research that are specifically important for this thesis are network effects and two-sided markets. These concepts provided foundational insights into how platforms operate and generate value (Katz & Shapiro, 1985; Rochet & Tirole, 2003; Parker & van Alstyne, 2005). Network externalities describe the impact the number of users of a service or product has on the value of that service or product to other users. Later in platform research, articles mainly speak of network effects, which is a type of network externality that describes the phenomenon where the value or utility of a service or product increases as more people use it. This concept highlights how individual adoption of a product enhances its overall value, thereby creating a positive feedback loop that encourages further adoption (Katz & Shapiro, 1985).

In the digital age, strong network effects serve as a key source of market power. Before the emergence of digital platforms, large pipeline businesses derived their market power from supply economies of scale. The term pipeline businesses describe businesses that use the classic value-chain model, where an input is transformed to a more valuable output (Alstyne et al., 2016). Take for example a car manufacturer. Manufacturing cars from raw materials comes with large fixed costs, which need a lot of starting capital to be overcome. A large, established company, however, is able to spread these fixed costs over an increasing number of buyers as the company grows even larger. Therefore, the growing scale of the company directly leads to improved margins. For platforms, on the other hand, market power is gained by expanding the network. More participants means a larger network, which increases the value a platform has due to network effects; the platform becomes more attractive because other people are already using it (Parker et al., 2016). In other words, the value of a platform is directly tied to the number of participants within its ecosystem.

Literature on two-sided markets aimed to explain this difference between traditional markets and platforms. Two-sided markets are markets in which a platform functions as an intermediary between two sides: the users and complementors. Interdependence between the two sides is emphasized in these markets as the success of one side is dependent on the participation of the other (Rysman, 2009). Network effects demonstrate that attracting more participants to one side increases the attractiveness of the other, thereby enhancing the platform's overall value. This dynamic, known as indirect network effects, incentivizes sponsors to employ strategies that subsidize one side to attract participants on the other, effectively growing the network as a whole. In some cases, this even involves offering free goods or services and incurring short term financial losses (Parker & van Alstyne, 2005). By leveraging network effects, platforms can grow their user base at a loss, with the expectation that the long term value generated by additional participants will outweigh the initial losses.

2.2 Platform strategy

Besides growing its platform, a sponsor needs to figure out how to outcompete other platforms trying to take a share of the market. Sponsors can take various approaches in their pursuit of increasing market power and dealing with competition. Eisenmann et al. (2006) were among the first to provide a clear overview of strategies employed by sponsors to navigate two-sided markets. This article identifies the challenges sponsors are faced with in two-sided markets and suggests how these challenges can be overcome in order to better their position in the market. It highlights how sponsors need to balance multiple factors like pricing strategy, winner-takes-all dynamics, and threat of envelopment to retain a growing ecosystem while dealing with potential competition. Important to notice is that these three challenges are examples of hurdles a sponsor must overcome in order for their platform to gain market power, but simultaneously puts the sponsor in a highly dominant position when done correctly. This is especially true when one platform comes out on top in a market with winner-takes-all dynamics, as this platform will then be able to enjoy a monopoly position and hold onto it with relative ease (Parker et al., 2016).

This same sponsor oriented perspective is taken in other exemplar articles published on this topic around this time, like the 2008 article published by Gawer & Cusumano. The article essentially combines previous research and practical knowledge from case studies on large platform companies to determine strategies for platforms to become leaders in their markets. It also underlines the importance of a stable ecosystem for the success of the platform. Although sponsors benefit from overall platform growth by creating beneficial conditions for the entire ecosystem, they are still competitive players with the end goal of making profit on their investments (Parker et al., 2016). While these earlier articles aimed to bridge theory with practice and offered strategic insights to sponsors, they overlooked the consequences of a continuously successful sponsor growing so dominant in its market and over its ecosystem that it becomes able to potentially abuse its power.

2.3 Dominant sponsors & platform governance

A dominant platform sponsor has “both incentive and ability to exert considerable influence to increase both the overall value created by the ecosystem and its own value capture” (Rietveld & Schilling, 2020, p. 1545). Sponsors in these positions of power over the ecosystem have become more prevalent over the past decade, especially with the rise of

‘Big Tech’ platforms such as Apple, Amazon, Facebook, Google, Microsoft, etc. To put it in perspective, these companies have become so large that they have surpassed many countries in wealth and influence (Gawer, 2021; Parker et al., 2016). Recent literature has paid more attention to the effects of a sponsor being this dominant, along with the governance they can freely conduct once in this position (Parker et al., 2016; Rietveld et al., 2020; Gawer, 2021). Scientific research has pointed out that two mechanisms are especially important to reach this position of dominance, namely network effects and switching costs. Network effects have already been identified as one of the core concepts within platform ecosystems. For a platform to be successful, a sponsor must seek to reinforce strong network effects (Parker et al., 2016). By initially attracting enough users and complementors to their platform, a company can secure a significant portion of the market by establishing itself as ‘the best option that everyone is already using’ (Parker & van Alstyne, 2005). To obtain this portion, a platform should provide technological features that are widely regarded as the most effective in fulfilling users' needs, but also provide sufficient complements and deploy the right market strategy (Rietveld et al., 2020). Once the platform reaches a critical user base, the same network effects that draw users towards the platform make it increasingly difficult to switch to other platforms (Farrell & Klemperer, 2007). As users invest time and resources, they become locked in, creating dependencies they are reluctant to abandon. This reluctance to leave the current platform and use another to fill the needs are called switching costs. High switching costs, such as abandoning a network that all your friends use or having to rebuild a digital library, further deter users from leaving, granting the sponsor more control over other ecosystem members (Parker et al., 2016).

The earlier mentioned threat of envelopment for growing platforms can become a weapon against competition once a sponsor has grown dominant in its respective market. Through enveloping potential competitors, a platform can further secure its dominance by removing rivals before they can become a serious threat (Eisenmann et al., 2006). By enlarging the gap between the platform and possible competitors, market entrenchment plays a critical role in maintaining dominance. As the dominant platform owns the majority of the market, it can leverage its large user base to negotiate favorable deals with the best complementors and enhance user experience more efficiently than competitors can (Cusumano et al., 2019). This creates a barrier to entry for new platforms, making it difficult to match the dominant platform. This is also where the concept of predatory pricing comes in. Although it was mentioned earlier that, through network effects, sponsors could rationalize offering products at a financial loss (Parker & van Alstyne, 2005), this strategy can also be used to offer goods or services at such low prices that less established competition can impossibly match them (Parker et al., 2016). Once a sponsor has gained and secured its position of dominance in the market using these strategies, it is then able to switch its attention towards maximizing the value it can take from it.

2.4 Value capture strategies

All sponsors need to capture value from their platform. A business that does not earn anything off the value it creates will have a hard time staying operational. How value is captured depends on which monetization strategy it adopted. Therefore, a sponsor must find a fitting strategy and know how it affects the ecosystem (Parker et al., 2016). A starting platform might have a difficult time finding ways to capture significant value without risking users and complementors looking for cheaper alternatives. A dominant sponsor with significant power over their market and ecosystem, however, is able to implement value capture strategies without having to worry as much about retaliation from other ecosystem members (Cusumano et al., 2019). This does not inherently mean that a sponsor will always choose to be exploitative. The interests of sponsors are sometimes aligned with the interests of other players in the ecosystem. Intel, for example, introduced its own designs in its complement market because it was not satisfied with the current state of innovation of complements on its platform (Gawer & Cusumano, 2002). While Intel's processing power became increasingly powerful, it was held back by the performance of its complements, like software and peripheral hardware. At first sight, this strategy could be interpreted as unfairly competing with complementors, but Intel merely seeked to improve the ecosystem by developing reference designs and software tools to help complementors optimize their products for the improved Intel processors. This intervention might have negatively impacted complementors short term, but improved the overall ecosystem long term.

In many other cases, the sponsor is able to get an increase in captured value without the other ecosystem member benefiting long term. This often proves to be a temptation difficult to resist (Gawer, 2021). Especially when the sponsor has grown dominant enough to the point where ecosystem members are sufficiently locked in, its main priority might switch to maintaining dominance while maximizing captured value, rather than growing the ecosystem and creating value (Rietveld & Schilling, 2020; Choi & Jeon, 2023). For different platform markets, there are different value capture strategies that could be effective. Building on how monetization of platforms is presented in Parker et al. (2016), three general value capture strategy categories can be determined that fit the scope and theoretical framework for this thesis. Variations within these categories exist, but the principle on how the sponsor is able to capture value remains the same.

2.4.1 Ad monetization

Ad monetization encompasses value capture strategies aimed at maximizing revenue through exposure to advertisements. By showing ads, a sponsor is able to keep the interactions on its platform between users and complementors cost free. Instead, users pay with their attention, which advertisers are often very willing to pay for, especially when they know whose attention they are receiving (Sabourin, 2016). At its core, capturing more value from ad monetization involves increasing the intrusiveness, frequency, or effectiveness of ads. In the most simple form, a sponsor increases the ad load by adding more advertisements, such as introducing ads during videos or in between songs.

2.4.2 Access monetization

Access monetization often describes value capture strategies that limit access to certain features, content, or services on the platform, offering them at a certain price to users. This approach leverages the platform's control over its ecosystem to create exclusivity or scarcity, incentivizing users to pay for enhanced access or functionalities, which might have been free to use on the platform earlier. A sponsor can choose to hide access to its platform entirely behind a membership or paywall, but this can hinder network effects from bringing in more participants (Parker et al., 2016). Oftentimes, the sponsor offers a free version with limited access, while reserving premium functionality for users which are further locked in (better known as a freemium model). By restricting access to certain features in the free version, network effects are less restricted while aiming to motivate more locked-in users to upgrade, thereby capturing additional value. The effectiveness of access monetization depends on the perceived value of the restricted features (Rietveld, 2017).

2.4.3 Data monetization

Data monetization is a category of value capture strategies where data is leveraged to generate revenue. This often involves selling user data to third parties, but can also help improve products, services, or business processes to indirectly capture value for the sponsor (see Baecker et al., 2020). Data monetization has become an increasingly important aspect of platform business models in the digital age, especially for platforms with large, engaged user bases. Some ecosystems rely solely on this form of value capture, where free services are offered in exchange for data (Gawer, 2021). The core mechanism of data monetization lies in the platform's ability to collect, analyze, and commercialize user interactions. Large platforms like Google and Facebook gather extensive data on user behavior and demographics. While data monetization offers significant financial benefits, it directly impacts users by raising concerns about privacy, autonomy, and trust (Zuboff, 2023). The collection and usage of data often occur in ways users are not fully aware of, which can quickly turn exploitative when data is used in ways users would never approve.

2.5 Effects on the ecosystem

Recent research has begun to explore how governance strategies of dominant sponsors evolve over time. Rietveld et al. (2020) show how governance by a sponsor changes as their dominance grows, emphasizing the effect this has on complementors. They noted that sponsors that place a high priority on maximizing shareholder value would shift their governance strategies towards increasing value capture. Simultaneously, they note that as the sponsor captures more value, this often takes away from the value other ecosystem members are able to get out of the platform. As Gawer (2021) noted, a platform that acts in such exploiting ways over time loses sight of how they managed to obtain their position of power in the first place and threatens the sustainability of the ecosystem, which will inevitably lead to its collapse. Therefore, such dominant sponsors will try to balance maximizing their value capture with the stability of the ecosystem, making very sure it does not destabilize beyond the point of collapse. This is a balance that is different for every market, as Knudsen & Belik (2023) point out that each platform has their own level of interconnection and sensitivity to network effects. Building on these insights, each platform has its own unique ecosystem that will shape a dominant sponsors' optimal balance between value capture and ecosystem stability.

To visualize the balance between value capture and ecosystem stability for various ecosystems and strategies, a causal influence diagram (CID) can serve as a powerful tool. CID's were originally created to map out systems and visualize the feedback loops that take place between the variables that drive it. The boxes in these models represent variables, while the arrows between the boxes point out a causal influence, being that negative or positive (Barbrook-Johnson & Penn, 2022). For this thesis, the CID is adapted to better visualize a platform ecosystem and the effect strategy implementation has on where value is distributed in the ecosystem. Therefore, the boxes represent the value that specific stakeholders place in the ecosystem, while the arrows indicate the influence the consequences of a strategy has on this value. By mapping out the relationships between the dominant sponsor, users, complementors, and other stakeholders, this adapted CID helps visualize how specific value capture strategies, discussed in the last subsection, affect value distribution of the ecosystem. The diagram helps illustrate key causal pathways and feedback loops among ecosystem members, clarifying both the direct and indirect impacts of a strategy.

This thesis takes ad load increase on YouTube as an example to demonstrate how the CID can be applied. YouTube is used to test this model since it can be considered a paradigmatic case. Paradigmatic cases operate as a reference point in its respective scientific field and may function as a foundation for further research (Flyvbjerg, 2006). For this thesis, YouTube is such a case due to their continued dominance in their market, high switching costs, and history of increased value capture through ad monetization in their freemium model (Alphabet, 2023; Pittock, 2023). A broader explanation for choosing the case of YouTube can be found in the methodology section.

Ads have always been present on YouTube, starting off as small banners and pop ups that could easily be ignored or clicked away. But over time, ads became more intrusive and YouTube started bundling them together as small commercial breaks that obscure the content being watched (Pittock, 2023; McCoy et al., 2008). The only two ways users are able to get rid of ads today are: using ad blockers, which don’t always work as YouTube and other content platforms actively try to thwart (Post & Sekharan, 2015) or, as part of the value capture strategy, paying for YouTube Premium. With the introduction of Premium, this change in ad strategy has captured more value for the sponsor by making a previously free option a paid service. This relatively straightforward increase in value capture makes YouTube a fitting example. A visualization of the effects of this strategy on YouTube’s platform ecosystem using a CID is shown in Figure 1.

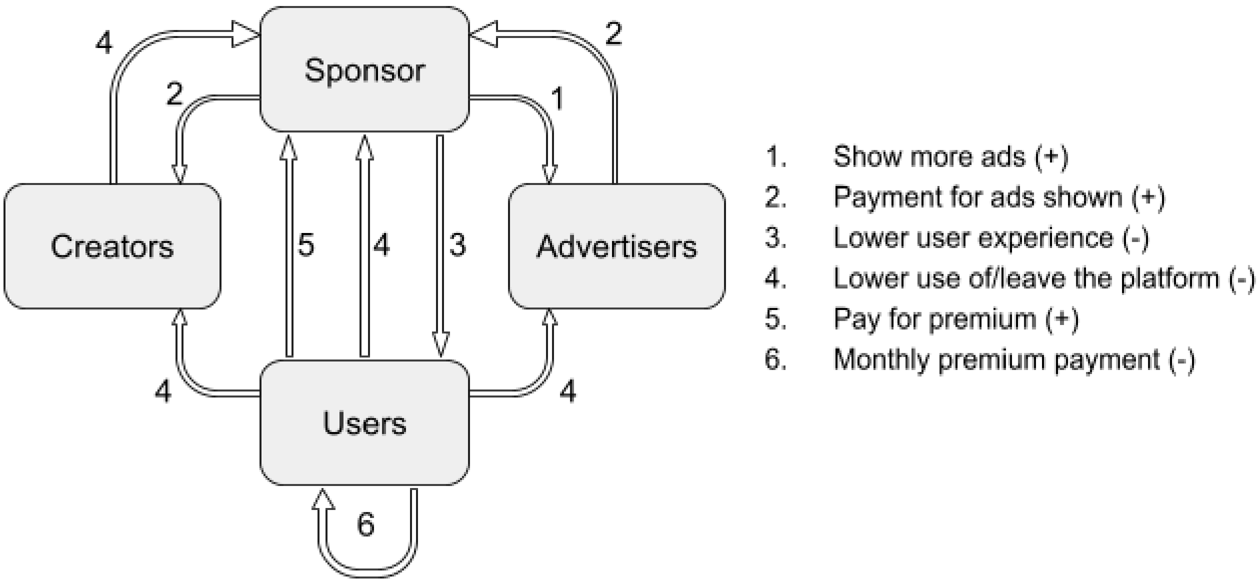

Figure 1: An adapted CID of the effect of ad load increase as a value capture strategy on the platform ecosystem of YouTube

By introducing more ads (1), the sponsor captures more value through increased payment from advertisers (2). This increase in captured value can potentially be used to benefit other ecosystem members as well, like the content creators, which are the complementors on this platform (2). Content creators will be drawn to the increased financial benefit on the platform, effectively boosting content offer and actually increasing the value of the platform for users (Parker et al., 2016; Eisenmann et al., 2006; Parker & Van Alstyne, 2005). However, even in this case, the added ad load could have a negative effect on user experience (3), since users now have to endure more ads per content consumed (Brajnik & Gabrielli, 2010). The magnitude of this effect depends on the users' perceived intrusiveness of the ads shown, with McCoy et al. (2008) stating that a higher online ad intrusiveness leads to higher irritation, which in turn negatively impacts the attitude towards the platform and lowers intention to revisit. This is tested in the experiment in this thesis to check whether the reaction to increased ad load is in line with earlier findings on this topic (McCoy et al., 2008; Choi & Jeon, 2023; Riedel et al., 2024) and an increased ad load does in fact negatively impact user enjoyment of online videos. Important to note is that enjoyment of the video is chosen here, rather than user experience or attitude towards the platform. This is because in the broader context of platform ecosystems, the strategy of increasing ad load does not necessarily have to result in a net degradation of user experience over time. If a sponsor decides to invest the added revenue in improving aspects of the platform that benefit the user in some way (higher pay for creators, improved user interface, investment in community, etc.), the negative effect on user experience can be mitigated and net user experience might stay equal or even improve (In this case, 3 becomes positive). This makes the strategy of increasing ad load in itself not exploitive, but rather what the added revenue is spent on. Therefore, to test if the ad load increase has an initially negative impact on users, the enjoyment of the video is taken as a proxy.

McCoy et al. (2008) conducted their experiment using a self made ecommerce website, which allowed for complete control over the experimental environment and precise monitoring of participant responses. While this setup ensured high internal validity for the impact of ads on participants, the artificial nature of the website does not translate well to dominant platform ecosystems. In their experiment, participants interacted with a platform they had no prior affiliation with, which eliminated any effects stemming from high switching costs typically associated with dominant platforms. As a result, their findings on ad intrusiveness were focused primarily on immediate user reactions rather than behavior influenced by platform dependency. In contrast, the experiment in this thesis seeks to replicate real-world conditions by situating participants within the context of YouTube, a dominant platform participants are familiar with and potentially have some level of lock-in with. This setup introduces an additional layer towards platform research, as participants' decisions to endure the increased ad load or lower use of the platform are now also influenced by their prior investment in the ecosystem.

This does not imply that this is the first time user responses to increased ad load have been investigated in the context of a specific platform such as YouTube (e.g., Yang et al., 2017; Puwandi et al., 2020; Arantes et al., 2018). The difference, however, is that prior studies have largely approached this issue from the perspective of advertisers, focusing on optimizing ad effectiveness and improving attitudes toward ads by analyzing user responses to different ad characteristics. Other literature has explored how freemium platforms can reduce ad intrusiveness to foster positive user attitudes (Riedel et al., 2024) and highlighted that overly intrusive or annoying ads can lead to disengagement, potentially harming ad revenue over time instead of increasing it (Goldstein et al., 2014). Unlike these studies, this thesis investigates user responses to ad load increases from the perspective of a platform ecosystem. Choi & Jeon (2023) actually address the same research topic (among other related topics) from a platform perspective, investigating how value capture through increasing ad load can lead to disengagement, where the balance is determined by a sponsor's dominance. While their work provides a theoretical analysis of macro level economic incentives driving value capture strategies and the effect they have on users, it does not empirically explore individual user responses and micro level decision-making in context of a specific platform. This leaves a gap to be filled by this thesis, which empirically investigates how individual users respond to such a strategy within the context of a real-world platform, where switching costs and network effects are able to influence their decision-making. Based on this gap, the following hypothesis is proposed:

H1: Users who experience a higher ad load are more likely to disengage from the platform than users who experience a lower ad load.

Because this hypothesis is proposed in the context of a dominant platform ecosystem, it gives insight beyond a users' psychological reaction to ads. By putting participants in a realistic situation regarding a platform they are involved with, this hypothesis tests whether the effects of increased ad load as a value capture strategy will actually result in user disengagement from the platform while accounting for switching costs and network effects.

Continuing with the example CID, a user faced with the increased ad load can react in three different ways: accepting the increased ad load, paying for premium, or disengaging (leaving or lowering use of) the platform. The first scenario will result in the arrows with number 4 and 5 having a magnitude of 0, meaning there is no direct response to the increased ad load. In this case, the user chooses to bear value being taken by the sponsor at his expense. This does not indicate that the user agrees with this shift in value, but rather chooses to remain passive. The second scenario will have a similar effect as the first, but the user mitigates the decreased user experience by accepting a monthly payment. Here, the user decides that the decrease in user experience outweighs the negative effect of a monthly premium payment (6). The third scenario, where the user chooses to reduce their usage or leave the platform entirely, can create a ripple effect that significantly impacts all other ecosystem members, especially if chosen by many. As users depart, the audience size for complementors decreases, diminishing their potential reach and ad revenue, undermining their motivation to continue producing content on the platform. With fewer engaged users, advertisers also suffer because the platform's value as an advertising channel declines, leading to a decrease in advertising demand (2 becomes smaller). This, in turn, affects the platform's revenue streams, as revenue from advertising makes up a significant portion of the sponsor's income (Alphabet, 2023).

With diminishing ad revenue and fewer engaged users, the sponsor may attempt to offset losses by either further increasing ad load or diversifying its revenue sources (Duan & Li, 2023). However, both actions can be detrimental. An increase in ad load might accelerate the deterioration of user experience even further, worsening the issue. Shifting revenue reliance could disrupt the platform's core offering and alienate users from the platform. A shift in revenue reliance would suggest a sponsor decreases value capture through one strategy, while increasing it through another. Imagine that YouTube got rid of ads on its platform entirely and chose to only operate on a subscription basis, like many large streaming platforms. Chances are that many users do not align with this revenue structure applied to YouTube and choose to abandon the platform.

Consequently, these effects of users disengagement can contribute to a cycle of diminishing returns: as user numbers drop, the platform's attractiveness to both complementors and advertisers decreases, further reducing the platform's value for remaining users. In the most extreme case, this scenario can destabilize the ecosystem to a point of collapse. When users are no longer willing to stay with the platform in its current state and/or have a better alternative, the same network effects that initially fostered growth start to work in reverse (Knudsen & Belik, 2023). A shrinking user base reduces the platform's value to complementors, which in turn might leave as well, creating negative direct and indirect network effects (Duan & Li, 2023). The platform, now lacking the engagement that once fueled its growth and profitability, may find it impossible to maintain its dominant position or even sustain its operations. This underscores the delicate balance a dominant sponsor must maintain between maximizing value capture and preserving a satisfied, engaged user base essential for ecosystem stability.

In practice, using an adapted CID to visualize and track the effects of implementing dominant sponsor strategies creates a general overview of the mechanisms working within an ecosystem and allows for comparative studies across platforms. While it demonstrates the specific impact of ad load increase on YouTube in this example, the model can readily be applied to other platforms and strategies, making it a versatile visualization tool in this part of platform research. Researchers and ecosystem members can apply these diagrams to give an overview of impact pathways and trade offs, but also find new insights on tipping point and possible strategies. While in the digital age, sponsors often already use predictive analyses and computer modeling before implementing major strategies, a CID can function as a versatile, accessible model that allows researchers or policy makers to systematically model and visualize the effects of dominant strategies across different platforms and contexts (McCarthy et al., 2022). It enables comparative analysis and hypothesis generation in cases where proprietary data is not readily available. CIDs might also serve as a foundational model that could be enhanced with data for more advanced computational simulations, making them a practical bridge toward more sophisticated quantitative research in platform studies (Barbrook-Johnson & Penn, 2022).

2.6 Switching costs and lock-in

When discussing the rise of a sponsor to a dominant position in the ecosystem and market, high switching costs were determined as a crucial factor in obtaining this position (Parker et al., 2016). High switching costs keep users from switching to possible competitors, creating a phenomenon called lock-in. Ultimately, if a dominant sponsor changes its strategic focus to maximizing value capture, the cost of switching is what keeps users from leaving the platform, even if the change in strategy has a negative effect on them (Chen & Hitt, 2002). The total switching costs are the sum of the many different costs that can occur when a user chooses to switch to a different platform. Farrell & Klemperer (2007) offer a broad explanation of switching costs and network effects, and their role in keeping customers from switching vendors. Although this article explains these concepts in an economical scope, they can be easily applied to platform dynamics as well. Switching costs are segmented into three primary types: psychological costs, learning costs, and transactional costs. Psychological costs encompass emotional attachment or habitual usage that makes users reluctant to switch. This could involve users’ comfort with the current platform interface or reluctance to move away from a familiar ecosystem, as well as brand loyalty. Learning costs are the costs associated with the time and effort needed to learn the use of a new platform, which can be high in hightech ecosystems where platform-specific knowledge is required. Besides the sunk cost of time that has already been invested into the platform they are currently using, users may feel deterred from switching to another platform due to the time investment required to again become proficient with another platform. Transactional costs include the tangible costs involved in switching, such as losing access to purchased content and complements or dealing with any financial penalties. For instance, if a user has paid for certain premium features on a platform, these would be forfeited upon switching. This can also work the other way, where joining another platform might require buying a subscription, which adds to the perceived cost of leaving. Even the incompatibility of data between two platforms and the inability to transfer this data would fall into this category.

Each platform ecosystem has its own level of switching costs that make up a combination of these three categories. In some of the largest companies in the world that own platforms, we see that sponsors leverage switching costs when implementing value capture strategies. This leveraging of switching costs is what drives ‘enshittifcation’, the earlier mentioned term coined by Cory Doctorow. He notes that many large platform companies that have established dominance show a shift in strategy towards maximizing value capture once ecosystem members become locked in (Doctorow, 2024). A clear example of this is Facebook, which shifted from a user focused social media platform to a profit oriented data-mining and ad-driven model. By relying on network effects in the form of users' emotional and social connections, as well as their accumulated content, Facebook created substantial switching costs. Users face not only the loss of their personal content and social networks but also the difficulty of rebuilding these on a different platform. This lock-in has allowed Facebook to increase ad load significantly, often displaying sponsored content over organic posts, without losing a significant portion of its user base (Doctorow, 2023).

Another great example is Amazon. Initially, Amazon focused on creating a large and loyal user base by offering benefits like low prices, free shipping through Prime, and extensive third-party options. As users invested more in the platform and media tied to the platform, Amazon solidified its dominant position while simultaneously putting competition out of business. This dominant position left complementors nowhere else to go other than Amazon if they wished to sell their goods online. Leveraging the control Amazon now had over the other ecosystem members, it raised seller fees and filled search results with paid ads (Doctorow, 2022). Scientific literature has yet to fully catch up to these cases and thoroughly analyze them, but some research like Zhu & Liu (2018) and Anderson & Bedre Defolie (2024) have tied real world dominant sponsor strategies to important concepts in platform literature. These articles examine the effects on the ecosystem when a sponsor aims to capture value by moving into the complement market, directly competing with complementors on its own platform. The case they have taken to examine this strategy was, again, Amazon. They find that Amazon looks for successful complements on its platform and creates its own version of the product, which is then pushed to the top of search results. This gives the products created by Amazon an unchallengeable competitive advantage and captures value directly away from complementors with popular products. Complementors faced with this strategy can either look for an alternative, which Amazon already outcompeted, or accept the situation. This shows how high switching costs on the platform have created a situation where ecosystem members are kept reliant on Amazon despite the degraded experience.

Similarly, YouTube has leveraged its dominant position and switching costs by increasing ad frequency and intrusiveness. Taking another look at the CID example, we determined that value capture by a dominant sponsor comes with the tradeoff of ecosystem stability. As long as switching costs are relatively high, the stability of an ecosystem will be less jeopardized by a value capture strategy than in an ecosystem with lower switching costs. This level of user lock-in can be described as the elasticity of the active user base. Originally rooted in classic economics, elasticity measures the responsiveness of demand to changes in price, or other influential factors (Marshall, 1920). Applied to platform ecosystems, the elasticity of the active user base reflects how sensitive users are to changes in the platform's value proposition. Specifically, whether they will tolerate adverse effects of changes in value capture strategy or choose to disengage from the platform.

When the active user base is inelastic, a high level of lock-in is present and users are less likely to react to increased value capture, even if their experience degrades. High switching costs and network effects make it costly for users to leave. This inelastic response can prevent a platform ecosystem from destabilizing. If an active user base is elastic, small changes in user experience, such as an increase in ads, are more likely to drive users away.

This higher elasticity appears in platforms with low switching costs and/or network effects, such as platforms in markets with good alternatives.

2.7 Premium as a 'buyout' option

In YouTube's case, extra value is captured through increasing ad load and restricting features for non-paying users (Pittock, 2023). Offering a premium subscription gives users the option to bypass the negative effects at the cost of a monthly fee, therefore 'buying out' of the new policy. This addition makes the value capture strategy of YouTube a combination between ad monetization and access monetization, also known as the freemium model. In this context, the premium service provides users with an ad free experience and enhanced features, counteracting the possible frustration caused by the sponsor's intensified ad monetization efforts. This setup allows users to choose which adverse effects they want to face, pay for access or watch ads. This could potentially help stabilize the ecosystem while still increasing value capture, as some users might be more likely to choose the premium option rather than disengaging from the platform due to the ads, effectively retaining some of the users that would have left without the premium option. The availability of a premium buyout option can therefore influence the elasticity of the installed base by potentially lowering the average sensitivity of users to value capture strategies. Offering premium not only provides an immediate buyout but also increases switching costs for those who subscribe. A user who pays for premium now has a financial stake in the platform through a recurring subscription, increasing their transactional switching costs and adding an additional layer of lock-in as long as this subscription can't be cancelled. This could even further entrench users who decided to pay for premium within the platform ecosystem, effectively reducing elasticity of the active user base.

When users are provided with a choice to pay for an improved experience and elimination of ads, they may be less likely to leave a dominant platform altogether, even if they are still dissatisfied with the sponsor's value capture efforts. A user that chooses to pay for premium automatically ties himself to the platform through a financial transaction, therefore avoiding disengagement in terms of partaking in the ecosystem. When a significant portion of users choose premium over disengaging from the platform in response to a value capture strategy such as increased ad load, it indicates that offering a premium service can act as a stabilizing factor, counteracting disengagement from ad monetization and decreasing the elasticity of the active user base. To test the role the option of purchasing a premium membership can have on users' likeliness to disengage from the platform, the following hypotheses are proposed:

H2a: When given the option to purchase a premium membership, users who experience a higher ad load are more likely to do so than users who experience a lower ad load.

H2b: Users who are more likely to disengage from the platform due to ads are more likely to purchase a premium membership than users who are less likely to disengage from the platform.

This hypothesis is split in two because they both need to be accepted in order to conclude that offering a premium membership has a stabilizing effect on the ecosystem that is caused by the increased ad load. H2a could be accepted when users who experience a higher ad load choose to purchase premium more often than people who experience a lower ad load, but this would have no stabilizing effect if the majority of these users never chose to disengage from the platform when the option of buying premium was not available. This hypothesis merely establishes whether there is a relationship between the ad load and likeliness to pay for premium. Alternatively, as we see in this thesis, H2b could be accepted and show that premium has a stabilizing effect when people who report a higher level of disengagement due to ads are more likely to purchase a premium membership, but this does not have to indicate that the ad load affects this relation. Therefore, this hypothesis examines whether there is a general relationship between likeliness to disengage from the platform and likeliness to pay for premium in the given ad load scenario, irrespective of the number of ads shown in the scenario.

2.8 Conclusion

The literature review of this thesis demonstrates that platform ecosystems operate as interconnected networks where network effects and switching costs emerge as critical mechanisms driving the dominance of platforms, allowing sponsors to leverage lock-in and entrench the market. However, as platforms grow increasingly dominant, sponsors face powerful incentives to shift their focus from fostering value creation to maximizing value capture, often at the expense of ecosystem stability.

Three value capture strategy categories were identified, while the concept of 'enshittification' was supported with scientific literature. The literature shows how dominant sponsors switch from value creation to value capture once users and complementors are sufficiently locked in. In these efforts, the balance between maximizing value capture and ecosystem stability is crucial for dominant sponsors. Excessive value extraction risks destabilizing ecosystems, creating a feedback loop of diminishing value and potential platform collapse.

The literature also underlines the contextual nature of platform dynamics. Strategies effective in one ecosystem may give different outcomes in another. A universal tool introduced to analyze value capture strategies in various platform ecosystems is the causal influence diagrams (CID), which offers a straightforward, practical approach to visualize the complex interdependencies within ecosystems. By looking at the disengagement of users as a response to a change in value capture, the elasticity of the active user base can give an idea on the average level of lock-in of users in the ecosystem. Overall, this literature review underscores the importance of understanding the trade-offs between value capture and ecosystem stability. These findings set the stage for the experiment conducted in this thesis, empirically testing the effects of a value capture strategy in a dominant platform ecosystem.

3. Methodology

This thesis aims to investigate the impact of value capture strategies by dominant platform sponsors, particularly focusing on user response. A literature review was conducted to establish a broader understanding of how dominant sponsors implement value capture strategies in various ecosystems, as well as creating a theoretical framework and conceptual model that effectively visualizes the effects on ecosystems. To test this model and quantitatively support the research- and second subquestion, an online survey-based experiment was conducted using YouTube as the platform setting. Through the experiment, primary data was gathered which provided an answer to the third subquestion: How does the introduction of a premium option influence the effect of a value capture strategy on users? The methodology section starts with a research design, which explains the choice of experiment and platform, afterwhich the conditions of the experiment are discussed. Then, the variables, participant selection, and data collection & analysis are explained. The methodology ends with a consideration of the limitations and possible ethical concerns.

3.1 Research design

3.1.1 Experiment & platform choice

Scientific literature in this field of platform research has given a clear idea of the mechanisms that act on platform ecosystems, but lacks empirical evidence on how these mechanisms specifically influence user behavior in real-world platform ecosystems. Particularly, the concept of dominant sponsors balancing platform collapse with value capture seems unexplored. Where platform sponsors in reality already rely on predictive analytics to weigh off strategies, scientific literature lacks insight into the different strategies and their impact on this balance, such as offering a premium membership (McCarthy et al., 2022). Conducting an experiment is therefore particularly valuable because it allows for a controlled and systematic investigation into the causal relationship between value capture strategies and user behavior within platform ecosystems (Bolinger et al., 2022). By being able to manipulate specific variables and directly observe their effects on users, a level of control is created that helps isolate the impact of such strategies, making it possible to draw more definitive conclusions on the effects of value capture with high internal validity. This helps to bridge the gap between theory and reality in platform governance.

As a large platform company, YouTube was a fitting candidate for the experimental setting. There are three points that make YouTube a paradigmatic case to test the theoretical framework proposed in the literature review: continued dominance in their market, high switching costs, and history of increased value capture through ad monetization in their freemium model (Flyvbjerg, 2006). YouTube has proven itself over the years as the leading video sharing platform, reaching around 2.5 billion monthly active users in 2024 (Solomons, 2024). With such a large network and no real competitors to take its place, it has created a level of lock-in which holds complementors and users tied to the platform. An additional benefit of this large user base is that it made finding participants relatively simple for this experiment. In 2023, YouTube reached an ad revenue of $31.5 billion, making up around two thirds of its entire revenue (Alphabet, 2023). This revenue dependency makes increasing ad load a highly likely strategy for YouTube to capture more value if they wished to do so. Combined with the fact that YouTube has leveraged ad increase in the past, it wouldn't be unrealistic that YouTube users might be faced with this strategy in the future (Pittock, 2023). Furthermore, ad load increase is a strategy that is significantly easier to test in an experiment than other value capture strategies, such as data monetization. The data platforms collect is often not publicly available, let alone what they do with this data.

3.1.2 Experimental conditions

The experiment was carried out using an online survey, where participants first had to watch a video containing ads, followed by 26 closed questions. The video was shown at the beginning of the experiment to mitigate any potential priming effects. After the video, the questions that provided crucial data to test the hypotheses were asked first. Less important questions were asked later in the survey to avoid survey fatigue or memory influencing the answers to the more important questions. To optimize the flow and questions and pretest the survey, cognitive interviews were conducted. These interviews also helped in the decision for appropriate ad load lengths for the control and treatment condition. The insights of these interviews can be found in Appendix A. The final version of the survey can be found in Appendix B.

To select the optimal video content for the experiment, it was essential to balance minimizing interference with the results from the video content while ensuring the chosen content reflected the level of engagement that is typical of videos on YouTube. Using the research of Bradley et al. (2001), which connects emotional responses to imagery, high arousal videos (videos that evoke exciting emotions such as joy or fear) were avoided. This stemmed from the idea that high arousal videos might take away attention from the ads, or create an emotional response to the video, which could interfere with participants' reaction to the ad load. On the other hand, Lang et al. (1995) found that positive, high arousal imagery tends to be remembered best by participants. This is in line with Guadagno et al. (2013), who determined that positive, high arousal videos are most likely to be forwarded by participants and therefore go viral. Combining this with advertisers' general avoidance of being associated with highly negative or offensive content (Kumar, 2019), a large incentive is created for YouTube's algorithm to prioritize positive, exciting content, making these types of videos more likely to be viewed on the platform. This creates a situation where, in reality, people often watch engaging, high arousal content on YouTube, while the validity of the experiment calls for a low arousal video. Therefore, to simulate an actual YouTube video that does not significantly take attention away from the ads or creates interfering emotional responses too extensively, a positive, neutral video category with moderate arousal needed to be picked. Additionally, the content category needed to appeal to participants of all ages and genders in order to mitigate potential demographic and engagement biases. Taking inspiration from other experiments and research into this topic, the category 'nature documentaries' was chosen as ideal for this experiment (Carvalho et al., 2012; Maffei et al., 2015). In other scientific literature, this content category gets rated as neutral content with high valence (level of positivity), moderate arousal, and appeals to all demographics. Within this category, high arousal or low valence videos (such as predator chases or deep sea videos) were avoided and a more calm clip of oceanic islands was taken. With permission, the YouTube video named ‘The Hidden World of Islands’ by Natural World Facts was picked for the experiment (link in Appendix C).

The choice of content for the ads in the experiment had a different approach. On YouTube, a huge variety of ads get shown to different users. Although the ads can be personalized for users by YouTube, the user has no control over the ads he gets shown. This makes it harder to establish which ad category is most fitting for the experiment. At the same time, this also makes it harder to find content that is relevant for all participants, as individual users get shown what is relevant to them specifically. Additionally, even if it was possible to find ads that are relevant for all participants and won’t interfere with participants’ reactions, permission would have to be granted from all owners. Therefore, to simplify this process while mitigating potential confounding variables caused by the ad content, randomization was used. This meant that each of the ads shown in the treatment group had an equal chance of showing up in the control group. To keep the experience as realistic as possible, ads were taken directly from YouTube that were listed under ‘Creative Commons’. This indicates that the content can be used for other purposes, as long as no profit is made by other parties, making them ideal for this experiment. The only remaining criteria were that the ads needed to be at least somewhat relevant to all participant demographics and equal in length. This resulted in four 30 second ads, which are listed in Appendix C.

Eventually, five different versions of the video were created that were identical, apart from the ads. The videos were edited to fit the experiment and uploaded to Vimeo in order to be embedded into the survey. In Vimeo, the playbar was removed and a timer on the video page was set so that participants could not skip the video. Participants who took part in the experiment had an equal, random chance of getting the control or treatment version. Within the control group, one of the four different control versions was randomly selected, which all had a total ad load of 30 seconds at the start of the video. The treatment group were shown one version with a total ad load of 120 seconds, divided into two blocks of 60 seconds. This division of ad load was chosen to best mimic how YouTube would divide ads on its platform (Goldman, 2022). Furthermore, the rest of the survey was kept identical for both groups. To keep time efficiency and response rates high, a cross sectional approach was taken where the results were compared between subjects. By including an actual YouTube video with ads shown on the platform, elements of mock behavior were included in the experiment, better simulating reality by letting participants experience the effect of increased ad load. However, since participants were asked to imagine what their response would be if the increased ad load applied to every video of similar length they watch on YouTube, the experiment was mainly intention based.

3.2 Variables

3.2.1 Dependent variable

The goal was to find out how YouTube users respond when confronted with an increased ad load as a value capture strategy. In the CID model, we determined three actions users could take in this situation, which were to leave or lower use of the platform, buy YouTube premium, or stay passive. Therefore, the primary dependent variable for this research combines these three actions into participants' likeliness to abandon or lower use of the platform, or simply *disengagement*. First, a scenario was sketched as follows: "From this moment, every video you watch on YouTube of similar length has the same number and duration of ads as in the video you just watched. YouTube Premium would also not be available. How likely would you be to take the following actions?" The data was gathered by proposing four possible actions participants might take in this scenario and asking their likeliness to take these actions on a 7-point likert scale matrix. These actions were: '*Stop using YouTube*', '*Lower my use of YouTube*', '*Increase my use of YouTube*' and '*Switch to another platform*'. Likert scale questions always had 7 points that used the same wording between the intervals (extremely, moderately, slightly, neutral, etc.), with 1 always being the most negative option and 7 the most positive. *Stop, switch and lower use* were aggregated to the latent variable *disengagement*. *Increase use* was included as a positive option to capture the broadest set of possible actions participants might take. Since it measures the direct opposite of '*lower use*', it is therefore not included in the aggregation. It also served to spot contradictions, as these two variables logically can never simultaneously have the answer 'likely'.

Furthermore, *willingness to pay for premium per month* (WTP) is later taken as a proxy to participants' likeliness to purchase a premium membership. People who purchase a premium membership choose to commit to the platform by avoiding negative effects of ads through paying a monthly fee instead, effectively negating disengagement that would have happened without this option. The variable *willingness_scenario* (WTP scenario) shows what price participants were maximum willing to pay for premium per month in the experiment scenario, with 1 being €0, increasing in steps of €2,50.

3.2.2 Independent variable

The initial independent variable used in this experiment is the *ad load*. The ad load represents the total duration of ads within the video and is a dichotomous variable: 0 for the control version and 1 for the treatment version. As described earlier, this variable simulates the introduction of increased ad load as a value capture strategy.

For the effect on *WTP in the experimental scenario*, *disengagement* was added as an independent variable. So for this analysis, the effect of *ad load*, as well as the effect of *disengagement* on *willingness_scenario* were explored.

3.2.3 Further variables

The WTP for premium in the given scenario can be influenced by a baseline WTP participants have for YouTube Premium in their regular experience. Therefore, to find out what price participants were maximum willing to pay for YouTube Premium in their regular experience with ads on YouTube, *willingness_regular* (WTP regular) was used. This variable used the same scale as *willingness_scenario*. *paid_subscriptions* was also added to show how willing participants are to pay for subscriptions on other, similar platforms.

To test whether the control version was perceived as an 'average' experience with ads, as well as testing if the treatment version was perceived as having a significantly higher ad load than usual, the variables *perceived_number* and *perceived_duration* were used. These variables measured the participants perceived duration and number of ads in the video compared with their usual experience with ads in videos. The variables *impact_enjoyment* and *impact_magnitude* were then introduced to find out what effect the manipulation had on participants. *impact_enjoyment* tested if the effect was negative or positive, while *impact_magnitude* tested how big this impact was compared to their regular experience. These variables all used a 7-point semantic differential with the same wording between the intervals (extremely, moderately, slightly, neutral, etc.), again with 1 always being the most negative option and 7 the most positive.

Some other control variables were introduced to capture various reasons participants could have that might influence their WTP or decision to disengage from the platform. To indicate how involved participants are with the platform, *youtube_usage* was created. This variable showed the amount of hours participants spend daily on YouTube, on average, with value one being 0 hours, increasing in steps of 30 minutes. The dichotomous variable *adblocker* was added, which had a value of one if participants were using an adblocker that allowed them to never watch ads on YouTube. In the same fashion, *currently_premium* provided if participants were currently using YouTube Premium, with premium users having the value one. *content_usage* shows which of the popular categories on YouTube participants watch mostly (Statista, 2024), but the only relevant data this variable provided for this thesis was to see if participants used YouTube for study or work. Participants who used YouTube for work or study were given the value one. *satisfaction_youtube* checked participants' overall satisfaction with YouTube as a platform. Furthermore, *ad_experience* showed their overall attitude towards ads. Lastly, *video_opinion* and *content_interest* were added to check how participants viewed the video in the experiment and the content category 'nature documentaries'. These four variables all used a 7-point semantic differential with the same setup as the earlier mentioned semantic differentials.

3.3 Participants

Two attention checks were included in the survey. For the first attention check, participants were presented with 8 animals and biomes and asked if they had seen them in the nature documentary. The answers contained 5 correct and 3 incorrect options. A perfect score yielded 8 points, while only selecting incorrect answers resulted in 0 points. Since randomly selecting answers would result in an average score of 4 points, participants had to obtain at least 5 points to be included in the analysis. For the second attention check, participants were asked to leave the question unanswered and continue with the next question, after which they were presented with an unrelated 7-point likert scale on satisfaction. Participants who answered this question were removed from the sample. Participants were also given a notice to check their internet connection and watch the video carefully to make sure they had a good working video and paid attention.

Using convenience sampling, people in The Netherlands were asked to participate in the experiment through text messages. No additional incentive for participation was offered. From the 89 participants who completed the survey, 4 participants were eliminated from the analysis for failing the first attention check. 4 more participants were eliminated from the analysis for failing the second attention check. The answers of the remaining 81 participants were checked for inconsistencies to the dependent variable statements. Participants that had answered “moderately likely” or “extremely likely” for the statement “increase use of YouTube”, while doing the same for “lower use of YouTube”, logically contradicted themselves. To avoid this contradiction stemming from a lack of attention during the experiment, participants with these answers were excluded from the analysis, resulting in 2 more eliminations.

The resulting sample contained 79 participants: 38 in the treatment group and 41 in the control group. In this sample, 3 participants had an incomplete survey (1 in control and 2 in treatment), but the answers they did submit were used in the analysis. Within the control group, the distribution of the 4 versions was as follows: 10 participants in control 1, 9 participants in control 2, 12 participants in control 3, 10 participants in control 4.

3.4 Data collection & analysis

Data was initially collected in the survey building interface Qualtrics. In the nominal multiple choice questions, randomization was used for the answer order. Randomization in question order was used as much as possible using the Qualtrics randomizer function, without disrupting the logical flow of the survey (the complete survey with survey flow can be found in Appendix B).

The results were exported from Qualtrics into an .sav file and analyzed in SPSS. Here, the descriptive statistics were determined and the manipulation was checked using one sample and independent sample t-tests. To test all hypotheses, two multiple linear regressions were utilized. This method was appropriate because it allows for the analysis of linear relationships between the independent and dependent variables, controlling for potential covariates. The regression model enabled the identification of significant predictors of participants’ behavioral responses, providing insights into the direct effects of the treatment condition.

3.5 Methodological limitations

Some other minor methodological limitations were present in the conducted experiment. First, since the experiment was not conducted in a lab setting but rather at participants’ own convenience, it was never guaranteed if participants actually watched the video and ads with full attention. The attention checks helped skim off participants who likely did not pay enough attention, but this is obviously never infallible. Second, confounding variables could also have potentially played a limiting role in this research. The control variables introduced helped mitigate this limitation as much as possible, but human behaviour in these situations is often a complex process which makes it impossible to control for every significant variable. Last, the description of YouTube Premium in the experiment only included an ad free experience. YouTube Premium has more functionalities in practice, which might make the service more attractive to participants and increase their WTP. However, these were omitted from the description to avoid confusion.

3.6 Ethical considerations

The necessary data for the experiment could be collected using only closed answer questions and required no further personal information besides age and gender. The participants could therefore remain anonymous, ensuring that the privacy of participants would not be jeopardized in case of a data breach. Furthermore, an opening statement was displayed at the beginning of the survey, which read that participants would automatically agree with the statement when clicking to the next page. The statement made participants aware of the topic of the experiment, what they would have to submit, what the possible risks were regarding data privacy, their freedom of leaving the survey unfinished or omitting questions they did not want to answer, and where they could ask potential questions about the experiment (the statement can be found in Appendix B). This opening statement, the required Data Management Plan, and the Human Research Ethics Checklist were all approved by the Human Research Ethics Committee of the TU Delft. The responses were saved on Qualtrics and later uploaded to a secured TU Delft OneDrive. After the research had concluded, all data was destroyed.

4. Results

This section presents the findings of the experiment and helps answer the research question: How do users respond to increased value capture by a dominant platform sponsors? The section starts off by introducing descriptive statistics of the data set, followed by a brief verification of the manipulation. Then, the hypotheses formulated in the research review will be tested using multiple linear regressions.

4.1 Descriptive statistics

Table 1 shows the distribution of characteristics. The sample consisted of 79 participants, with 57.0% identifying as male and 43.0% as female which were relatively balanced between the control group (63.4% male) and the treatment group (50% male). Participants were diverse in age, ranging from 18 to 65+. The largest age group was 25–34 years, comprising 39.2% of the full sample. The age distribution was generally consistent across the control and treatment groups, with minor variations. The majority of participants reported watching YouTube for less than one hour daily. Specifically, 48.1% watched for 0–0.5 hours, while 25.3% reported 0.5–1 hour. Notably, 18.4% of the treatment group reported no daily YouTube usage, compared to 9.8% in the control group. Just 10 participants reported using YouTube longer than an hour on average daily. Only 2 participants reported being Premium subscribers, equally distributed between the two groups. Due to this number being so low and equally distributed in the sample, premium use was omitted as a control in the regressions. Half of the participants (50.6%) reported using YouTube for study or work purposes, with similar proportions in both groups (51.2% in control, 50% in treatment).

Table 2 shows the descriptive statistics of ordinal variables in the dataset. In this table, we see that the treatment group reported higher intentions to stop using YouTube (M = 4.86, SD = 2.03) than the control group (M = 3.54, SD = 2.25), as well as their intentions to lower their use of YouTube (M = 6.22, SD = 1.27) compared to the control group (M = 4.83, SD = 1.94), and switching to alternative platforms (M = 5.53, SD = 1.81) than those in the control group (M = 4.24, SD = 2.05). In contrast, intentions to increase use of YouTube were low in both groups, with the treatment group reporting an even lower mean (M = 1.46, SD = 0.73) than the control group (M = 1.95, SD = 1.30). For regular scenarios, the mean willingness to pay was slightly lower in the treatment group (M = 1.76, SD = 0.97) compared to the control group (M = 1.98, SD = 1.13). For the experimental scenario, willingness to pay was similar across both groups (M = 2.47 in treatment, M = 2.46 in control). The treatment group expressed slightly lower satisfaction with YouTube (M = 4.92, SD = 1.30) compared to the control group (M = 5.29, SD = 1.19). Additionally, the treatment group exhibited a more negative attitude towards ads (M = 1.66, SD = 0.88) than the control group (M = 2.05, SD = 0.87). Participants in both groups generally rated the experimental video and its category positively.

Table 1: Demographic characteristics

Variable	Control		Treatment		Full Sample	
	N	*%*	*N*	*%*	*N*	*%*
Gender						
Male	26	63.4	19	50	45	57.0
Female	15	36.6	19	50	34	43.0
Age						
18–24	7	17.1	7	18.4	14	17.7
25–34	18	43.9	13	34.2	31	39.2
35–44	5	12.2	2	5.3	7	8.9
45–54	3	7.3	4	10.5	7	8.9
55–64	5	12.2	8	21.1	13	16.5
65+	3	7.3	4	10.5	7	8.9
Daily YouTube usage						
0 hours	4	9.8	7	18.4	11	13.9
0–0.5 hours	22	53.7	16	42.1	38	48.1
0.5–1 hour	11	26.8	9	23.7	20	25.3
1–1.5 hours	4	9.8	0	0	4	5.1
1.5–2 hours	0	0	4	10.5	4	5.1
2–2.5 hours	0	0	1	2.6	1	1.3
2.5–3 hours	0	0	1	2.6	1	1.3
Premium users	1	2.4	1	2.6	2	2.5
Adblocker users	6	14.6	7	18.4	13	16.5
Uses YouTube for study/work	21	51.2	19	50	40	50.6

Table 2: Descriptive statistics

Variable	Control					Treatment				
	M	*SD*	*Min*	*Max*	*N*	*M*	*SD*	*Min*	*Max*	*N*
Stop using YouTube	3.54	2.248	1	7	41	4.86	2.030	1	7	37
Lower use of YouTube	4.83	1.935	1	7	41	6.22	1.272	2	7	37
Increase use of YouTube	1.95	1.300	1	5	40	1.46	.730	1	3	37
Switch to other platform	4.24	2.047	1	7	41	5.53	1.812	1	7	38
Willingness to pay for Premium monthly (regular)	1.98	1.129	1	5	41	1.76	.971	1	4	38
Willingness to pay for Premium monthly (scenario)	2.46	1.567	1	7	41	2.47	1.447	1	7	38
Satisfaction with YouTube	5.29	1.188	2	7	41	4.92	1.299	1	7	37
Regular attitude towards ads	2.05	.865	1	5	41	1.66	.878	1	5	38
Opinion on experiment video	5.59	.921	3	7	41	5.55	1.288	1	7	38
Opinion on video category	5.59	1.284	2	7	41	5.76	1.025	2	7	38

4.2 Manipulation

4.2.1 Perceived ad duration and number in control group

To verify the baseline ad perceptions of participants in the control group, a one-sample t-test was conducted with the test value set at 4, which represented that the ad duration and number in the experiment video were perceived as "average". The results for the perceived duration of ads ($M = 4.44$, $SD = 1.205$, $N = 41$) showed a significant difference from the test value of 4 ($t(40) = 2.333$, $df = 40$, $p = .025$), with a mean difference of 0.439 (95% CL [0.06, 0.82]. This indicates that perception of the duration of ads in the control group leaned towards slightly above average. Conversely, the results for the perceived number of ads ($M = 3.54$, $SD = 1.051$, $N = 41$) showed a significant difference in the opposite direction ($t(40) = -2.823$, $df = 40$, $p = .007$), with a mean difference of -0.463 (95% CL [-0.80, -0.13]. This suggests that perception of the number of ads in the control group leaned towards slightly below average.

4.2.2 Perceived ad duration and number between condition groups

To verify whether participants in the treatment group perceived the duration and number of ads compared to the control group as significantly higher, an independent samples t-test was performed for the variables *perceived_duration* and *perceived_number*. For the perceived duration of ads, the results indicate a significant difference between the control group and the treatment group ($t(77) = -4.518$, $p < .001$). Levene's test showed that the assumption of equal variances was met ($F = 0.04$, $p = .843$). The mean difference of -1.166 (95% CI [-1.680, -0.652]) confirms that participants in the treatment group perceived the duration of ads to be significantly higher. For the perceived number of ads, the results also show a significant difference between the control group and the treatment group ($t(77) = -12.071$, $p < .001$). Levene's test for equality of variances was again non-significant ($F = 1.372$, $p = .245$), indicating that equal variances can be assumed. The mean difference of -2.674 (95% CI [-3.115, -2.233]) further supports that participants in the treatment group perceived the number of ads as significantly higher.

4.2.3 Effect of increased ad load on enjoyment

An independent samples t-test showed a significant difference for impact on enjoyment between the control group and treatment group. Levene's test for equality of variances confirmed equal variances ($F = 0.150$, $p = 0.700$). The result was significant ($t(77) = 5.528$, $p < 0.001$), indicating that the treatment group experienced a significantly greater negative impact on their enjoyment compared to the control group. The mean difference was 1.298 (95% CI [0.831, 1.766]), meaning the effect was statistically significant. For the magnitude of impact, the analysis revealed a weaker effect. Levene's Test indicated that equal variances could not be assumed ($F = 7.689$, $p = 0.007$), so unequal variances was used. The result neared significance ($t(67.909) = -1.650$, $p = 0.052$) for a one-sided test, but the effect was not significant for a two-sided test ($p = 0.104$). The mean difference was -0.564 (95% CI of [-1.245, 0.118]).

4.3 Hypothesis testing

To assess the reliability of the latent variable *disengagement*, Cronbach's alpha was calculated for the three aggregated variables (*likeliness_to_stop*, *likeliness_to_leave*, *likeliness_to_switch*). This resulted in a Cronbach's alpha of .852, indicating high internal consistency among the items. Simple aggregation was used to calculate the value for disengagement, taking the sum of the three variables and dividing by three.

Table 3 presents the results of the multiple linear regression to predict disengagement. In Model 1, only the control variables are included, while Model 2 shows the full model with ad load.

Table 3: Effect on disengagement

	Dependent variable = *disengagement*	
Variables	**Model 1**	**Model 2**
Controls		
Age	0.363*** (0.132)	0.324** (0.126)
Gender	0.057 (0.465)	-0.235 (0.454)
Satisfaction with YouTube	-0.044 (0.179)	0.008 (0.171)
Attitude towards ads	-0.332 (0.234)	-0.193 (0.228)
Adblocker usage	0.290 (0.557)	0.207 (0.531)
Daily YouTube usage	0.207 (0.201)	0.053 (0.199)
Uses YouTube for study/work	-0.213 (0.400)	-0.177 (0.381)
Predictors		
Ad load condition		1.162*** (0.405)
Adjusted R^2	0.056	0.145
F	1.653	2.627**

**** = p < 0.01 ** = p < 0.05 * = p < 0.1*

The overall fit of the model improves in Model 2, indicating that Model 2 better fits the data. Model 2 is also statistically significant (p = 0.014) while Model 2 is not (p = 0.135). The ad load condition proved to be positively correlated with disengagement (p = 0.005), with participants in the higher ad load condition reporting increased disengagement compared to those in the lower ad load condition. These results therefore provide support for H1. Besides the condition, the control variable for age also proved to be a significant predictor ($p = 0.012$), with older participants showing higher levels of disengagement. An explanation for the significance of age as a predictor could be attributed to older participants simply being less influenced by switching costs on YouTube, making them disengage from the platform more easily. However, other reasons, like overall higher sensitivity to ad load compared to the younger generations, could also explain this significance as well.

To examine the effect of ad load and disengagement on WTP in the scenario, another multiple linear regression was conducted, shown in Table 4. The results indicate that although the ad load condition has a positive effect on WTP in the scenario, this result is not statistically significant ($p = 0.278$). Furthermore, introducing ad load as a predictor barely improves the model. This indicates that variations in ad load do not directly influence participants' WTP for premium. However, disengagement is found to significantly increase WTP in the scenario ($p = 0.005$), supporting that a higher disengagement leads to a greater WTP in the scenario. The inclusion of disengagement increases the model's explanatory power, as reflected in the adjusted R^2 value. The insignificant effect of ad load on WTP in the scenario shows that a higher ad load does not directly motivate participants to increase their WTP in the scenario, while a higher likeliness of disengaging does motivate participants to increase their WTP in the scenario. This results in the rejection of H2a but acceptance of H2b.

The significance and consistency of WTP regular as a predictor highlights the importance of users' baseline WTP when considering WTP in the experimental scenario. In all models, satisfaction with YouTube remains a significant and positive predictor of WTP in the scenario. This is also true for attitude towards ads, which remains a significant negative predictor. This shows that a higher satisfaction with the platform and higher general annoyance towards ads result in a higher WTP in the scenario.

Table 4: Effect on willingness to pay in the experimental scenario

	Dependent variable = *WTP scenario*		
Variables	**Model 1**	**Model 2**	**Model 3**
Controls			
Age	-0.054 (0.069)	-0.062 (0.069)	-0.113 (0.069)
Gender	-0.009 (0.239)	-0.069 (0.245)	-0.019 (0.227)
Satisfaction with YouTube	0.193** (0.095)	0.202** (0.095)	0.191* (0.090)
Attitude towards ads	-0.265** (0.121)	-0.238* (0.123)	-0.214* (0.116)
Adblocker usage	-0.117 (0.293)	-0.140 (0.293)	-0.197 (0.279)
Daily YouTube usage	0.187* (0.104)	0.156 (0.108)	0.152 (0.100)
Uses YouTube for study/work	0.289 (0.206)	0.296 (0.206)	0.326 (0.196)
WTP for Premium monthly (regular)	1.001*** (0.106)	1.008*** (0.106)	1.041*** (0.102)
Paid subscriptions on similar platforms	0.013 (0.055)	0.016 (0.055)	0.028 (0.052)
Predictors			
Ad load condition		0.239 (0.219)	
Disengagement			0.172*** (0.059)
Adjusted R^2	0.653	0.654	0.687
F	17.083***	15.538***	17.921***

*** = $p < 0.01$ ** = $p < 0.05$ * = $p < 0.1$

5. Discussion & Conclusions

This study set out to examine how users in a dominant platform ecosystem respond to increased value capture by a dominant sponsor, using increased ad load on YouTube as a paradigmatic case. Specifically, the experiment tested the effects of increased ad load as a value capture strategy on user disengagement and explored whether the introduction of a premium option could mitigate these effects. The findings provide valuable insights into user behavior within the context of a platform ecosystem characterized by high levels of lock-in and limited alternatives. The results confirm that a significant increase in ad load negatively impacts user enjoyment and drives disengagement. Regarding the effect on WTP in the given ad load scenario, the data shows that users who are more likely to disengage were also more likely to purchase a premium membership, suggesting that these participants are willing to purchase a premium membership to avoid disengaging from the platform. However, the increased ad load did not have a significant causal effect on WTP for premium. Instead, premium buyers are generally more ad averse, irrespective of the ad load. This suggests that people willing to pay for premium are dissatisfied with ads in general, regardless of whether the ad load is normal or excessive.

The findings of this study reveal several important patterns and relationships that warrant further discussion. First, the observed relation between increased ad load and user disengagement aligns with existing theories on ad intrusiveness and its effects on user satisfaction (McCoy et al. 2008; Choi & Jeon, 2023; Riedel et al., 2024). The strong statistical significance of the ad load condition as a predictor of disengagement confirms its anticipated effect as a value capture strategy on users within a platform ecosystem. These results therefore confirm that increased ad load drives users to either reduce their engagement or consider abandoning the platform entirely. Where the findings of McCoy et al. (2008) and Choi & Jeon (2023) essentially differ from the findings of the experiment in this thesis, is that participants' decision-making was subjected to the presence of potential switching costs and network effects. By linking the experiment specifically to a dominant platform like YouTube, the context of the findings go beyond psychological and economical research and enter the domain of platform research.

The effects of ad load and disengagement on the WTP for premium were partially consistent with expectations. While it was anticipated that participants would have a higher WTP in the experimental scenario to avoid disengagement, the findings indicated that ad load actually did not have a significant impact on the WTP in the experimental scenario. This suggests that the decision to buy premium might stem from a baseline aversion towards ads rather than being directly proportional to the received ad load. Participants with a relatively high WTP for premium in the experimental scenario seem to fall into a category of users who are predisposed to avoiding ads altogether. These users may tolerate some ad load, but see premium as a solution to a frustration that exists independently of the number of ads they get shown. The statement that disengaged users would buy premium as a stabilizing mechanism was supported, but this relation proved independent of ad load. The experiment shows that including premium as a buyout option from the adverse effects of ad load increase can reduce the elasticity of the active users base, but this effect stemmed from a group of participants that want to avoid ads altogether, regardless of the ad load.

5.1 Theoretical implications

This thesis started off by identifying a critical gap in platform research. Recent literature on this topic has mainly focussed on increased value capture by dominant sponsors and the effect this has on the ecosystem as a whole (e.g. Gawer, 2021; Rietveld & Schilling, 2020), or complementors specifically (e.g. Zhu & Liu, 2018; Rietveld et al., 2020). This thesis adds to this body of knowledge by focussing on users specifically, highlighting their role in dominant platform ecosystems. By combining platform research with behavioral research, this thesis demonstrates how individual user decision-making at micro level can lead to significant macro level impacts on platform ecosystems. Prior studies often analyze value capture from either a strategic management perspective or a user experience perspective, but this research empirically demonstrates how platform-wide monetization strategies directly shape user retention and engagement. While observational and theoretical studies on dominant platforms (e.g., Choi & Jeon, 2023; Gawer, 2021; Anderson & Bedre Defolie, 2024) provide valuable insights, they lack the ability to empirically test causal relationships due to limited control over variables. By employing an experiment, this research was able to isolate the effects of a value capture strategy on user behavior in a dominant platform ecosystem, thereby establishing causality between the dependent and independent variables in a controlled yet realistic setting.

This study builds on literature by Parker et al. (2016) and Rietveld & Schilling (2020) towards further insights into the trade-offs of value capture strategies with ecosystem stability. By exploring ad load as a specific strategy on YouTube, the findings link theory to practice, but emphasize the context-dependent nature of the topic. The theoretical framework created in this thesis is based on established literature from platform research, but offers several tools to deductively analyze specific cases of present-day dominant platforms. One of these tools is the CID model, which serves as an intuitive and transparent visualization tool to map out causal pathways and feedback loops within a platform ecosystem. The experiment demonstrated the practical applicability of the CID model in tracing the ripple effect of increased ad load on user behavior. Its accessibility without the need for specialized technical knowledge make it a counterbalance to current-day advanced predictive models which platform sponsors use to maximize value capture (McCarthy et al., 2022).

5.2 Practical implications

This thesis gives insightful practical implications for platform sponsors, policymakers, and other ecosystem members. First, the findings extend Doctorow's journalistic work on 'enshittification' by empirically demonstrating how increased value capture by dominant sponsors in the case of YouTube affects user experience and engagement. While Doctorow's work provides a compelling narrative of how platforms shift from value creation to maximizing value capture as ecosystem members become locked in, this thesis adds rigor by offering quantitative evidence of these dynamics. Specifically, this research enriches the understanding of how dominant sponsors leverage user lock-in and highlights the risks of over-extraction, offering evidence for the balancing required between value capture and overall ecosystem prosperity.

As described in the literature review, maximizing value capture in dominant platform ecosystems can generate fast, short term revenue, but poses a long term risk to ecosystem stability. The experiment in this thesis confirms this idea, since participants presented with four times the regular ad load were significantly likely to disengage, even from an ecosystem characterized by high switching costs. Sponsors must carefully balance these trade-offs by monitoring the long and short term effects on their ecosystems and adjusting value capture strategies accordingly. Sponsors monetizing the interactions on their platform is a core mechanism of platform ecosystems, but simply taking as much as switching costs allow to take is not a sustainable strategy and will ultimately lead to detrimental outcomes for all ecosystem members (Gawer, 2021). Ideas of reinvesting captured value into user-focused improvements, such as increasing complement quality or enhanced features, are presented in this thesis as a way of capturing value while reinvesting some of this value back into the ecosystem.

Premium subscriptions can serve as a stabilizing mechanism for retaining users, but their success depends on meeting user expectations and needs. The findings of the experiment suggest that sponsors might have more success tailoring premium services to specific demographics rather than simply using them as a general buyout option for increased ad load, therefore adding value beyond ad free experiences through improved functionalities. This further solidifies the shift in platform research of putting more focus on the heterogeneity of user demands (Rietveld & Schilling, 2020).

Policymakers should consider the risks posed by excessive value capture strategies from dominant sponsors to both competition and user welfare. A sponsor that is able to acquire a significant amount of market power while simultaneously locking out competition is completely free to shift governance in its own favor, disregarding the effect on the market and users (Choi & Jeon, 2023). Policymakers should therefore aim to increase competition and set limits to value capture strategies to protect users. Moreover, regulations should improve transparency in monetization strategies, as users are oftentimes insufficiently informed on how a sponsor captures value from the platform, especially in the domain of data monetization (Gawer, 2021). Maintaining ecosystem sustainability requires a governance model that goes beyond maximizing shareholder value and values sustainability and ethical considerations as well. By centering policies around user trust and engagement, sponsors are incentivized to shift their focus towards fostering long term user loyalty and ecosystem sustainability instead of short term gains.

5.3 Limitations

While this study offers valuable insights into an underexplored topic in platform research, several limitations must be acknowledged to contextualize the findings and their generalizability. One key limitation is the hypothetical nature of the experimental setup. Although efforts were made to replicate realistic conditions through visualization of the scenario, using an authentic YouTube video and ads, participants' responses were based on intentions rather than actual behavior. This introduces the possibility of an intention-behavior gap, where participants might overestimate or underestimate their reactions (to increased ad load or WTP for premium in the experimental setting) in the experiment compared to the same scenario in reality. The experiments’ reliance on self reported data also allowed for potential response biases. Participants may have tailored their responses to align with perceived expectations or struggled to accurately recall their typical YouTube experiences. These biases can never be fully eliminated with the chosen methodology and should be considered when interpreting the findings.

Another limitation concerns the geographic and demographic scope of the study. By using convenience sampling, the participant pool was mostly limited to people from the Netherlands, which may not fully capture global platform usage and ad tolerance. The decision to use convenience sampling was made in consideration with the time and resources available for this research. However, this does introduce potential sampling and self-selection biases, while restricting the broader applicability of the findings to other regions. The demographic distribution of the sample came close to the distribution of YouTube users globally, but this is not enough to make any meaningful claims in this direction (Kemp, 2023). The choice for convenience sampling, combined with these limitations, makes generalizability to the target population very difficult, but insightful conclusions about the analyzed sample can still be drawn due to high control over the variables and internal validity of the experiment.

Moreover, the choice to focus on YouTube and ad load as the sole case and strategy limits the generalizability of the conceptual model to other platforms and value capture strategies. While YouTube's clear dominance, high switching costs, and history of increased value capture make it a fitting case to test the model, ecosystems with different structures and value capture strategies may exhibit completely different dynamics. Therefore, the versatility of the theoretical framework can be proven in future research by testing it on several other cases across various platforms and strategies. In light of the limitations, the findings should be interpreted as a foundational step towards understanding user responses to increased value capture in a dominant platform ecosystem rather than definitive evidence.

Despite its limitations, the experimental approach provided unique advantages over alternative methods. A Survey alone would not have allowed for direct exposure to increased ad load, and observational studies could not have isolated causal effects due to external confounding factors. The experimental setting ensured that responses were measured under controlled conditions, making it a strong choice for taking an essential step in establishing causality between value capture strategies and user disengagement.

5.4 Future research

Future research addressing the limitations could strengthen the validity and applicability of the conceptual model by investigating the effects of alternative value capture strategies, especially those using access- and data-monetization. Comparing user responses to different value capture strategies across various platform ecosystems would provide a broader understanding of this topic. Applying the framework and CID model to other platforms could help improve the framework and uncover unique dynamics. Combined with examining other factors that could influence the elasticity of the active user base, future research can help improve the generalizability of the theoretical framework proposed in this thesis. This process can work in conjunction with scientifically analyzing more cases of dominant sponsors maximizing their value capture, as in studies like Zhu & Liu (2018). When more of these cases are empirically researched rather than journalistically discussed, important conclusions can be drawn which can aid in broadening the understanding of these dynamics. This, in turn, can help policy makers better regulate dominant platform ecosystems.

Conducting longitudinal studies using similar experiments could provide more insights into user responses and their evolution over time. This research could help answer questions like: How definitive is a users’ decision to disengage from a dominant platform over time? Do user and sponsor interactions change when a platform comes closer to collapse? Or, as proposed in Rietveld & Schilling (2020): When do sponsors switch from creating value to capturing most of the value? Future research aiming to answer these research questions can build on the insights provided by this thesis, advancing both theoretical and practical understanding of governance and value capture in dominant platform ecosystems.

6. References

Alphabet (2023). Annual filings 2023. Alphabet Investor Relations. https://abc.xyz/investor/sec-filings/annual-filings/2023/

Alstyne, M. W. van, Parker, G. G., & Choudary, S. P. (2016). Pipelines, platforms, and the new rules of strategy. Harvard business review, 94(4), 54-62.

Alstyne, M. W. van, Gu, G., & Finger, D. (2023). Why customers leave platforms — and how to retain them. Harvard Business Review. https://hbr.org/2023/08/why-customers-leave-platforms-and-how-to-retain-them

Anderson, S., & Bedre Defolie, Ö. (2024). Hybrid platform model: Monopolistic competition and a dominant firm. The RAND journal of economics, 55(4), 684-718.

Arantes, M., Figueiredo, F., Almeida, J. M., & Prates, R. O. (2018). An investigation of user actions and experiences when exposed to YouTube video ads. In Proceedings of the 24th Brazilian Symposium on Multimedia and the Web (pp. 283-290).

Baecker, J., Engert, M., Pfaff, M., & Krcmar, H. (2020). Business Strategies for Data Monetization: Deriving Insights from Practice. In Wirtschaftsinformatik (Zentrale Tracks) (pp. 972-987).

Barbrook-Johnson, P., & Penn, A. S. (2022). Systems Mapping: How to build and use causal models of systems (p. 186). Springer Nature.

Bradley, M. M., Codispoti, M., Cuthbert, B. N., & Lang, P. J. (2001). Emotion and motivation I: defensive and appetitive reactions in picture processing. Emotion, 1(3), 276.

Brajnik, G., & Gabrielli, S. (2010). A review of online advertising effects on the user experience. International Journal of Human-Computer Interaction, 26(10), 971-997.

Bolinger, M. T., Josefy, M. A., Stevenson, R., & Hitt, M. A. (2022). Experiments in strategy research: A critical review and future research opportunities. Journal of Management, 48(1), 77-113.

Carvalho, S., Leite, J., Galdo-Álvarez, S., & Gonçalves, Ó. F. (2012). The Emotional Movie Database (EMDB): A Self-Report and Psychophysiological Study. Applied Psychophysiology and Biofeedback, 37(4), 279–294.

Chen, P. Y., & Hitt, L. M. (2002). Measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. Information systems research, 13(3), 255-274.

Choi, J. P., & Jeon, D. S. (2023). Platform design biases in ad‐funded two‐sided markets. The RAND Journal of Economics, 54(2), 240-267.

Cusumano, M. A., Gawer, A., & Yoffie, D. B. (2019). The business of platforms: Strategy in the age of digital competition, innovation, and power (Vol. 320). New York: Harper Business.

Confessore, N. (2018). Cambridge Analytica and Facebook: The Scandal and the Fallout So Far. The New York Times. https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html

Doctorow, C. (2022). How monopoly enshittified Amazon. Medium. https://doctorow.medium.com/how-monopoly-enshittified-amazon-83f42a585c3c

Doctorow, C. (2023). The ‘Enshittification’ of TikTok. WIRED. https://www.wired.com/story/tiktok-platforms-cory-doctorow/

Doctorow, C. (2024). ‘Enshittification’ is coming for absolutely everything. Financial Times. https://www.ft.com/content/6fb1602d-a08b-4a8c-bac0-047b7d64aba5
Duan, W., & Li, C. (2023). Be alert to dangers: Collapse and avoidance strategies of platform ecosystems. Journal of Business Research, 162, 113869.
Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. Harvard business review, 84(10), 92.
European Commission. (2017). Antitrust: Commission fines Google €2.42 billion for abusing dominance as search engine by giving illegal advantage to own comparison shopping service. European Commission. https://ec.europa.eu/commission/presscorner/detail/en/ip_17_1784
Farrell, J., & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. Handbook of Industrial Organization.
Flyvbjerg, B. (2006). Five misunderstandings about case-study research. Qualitative inquiry, 12(2), 219-245.
Gawer, A. (2021). Digital platforms and ecosystems: remarks on the dominant organizational forms of the digital age. Innovation, 24(1), 110-124.
Gawer, A., & Cusumano, M. A. (2002). Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation (Vol. 5, pp. 29-30). Boston: Harvard Business School Press.
Gawer, A., & Cusumano, M. A. (2008). How companies become platform leaders. MIT Sloan management review.
Goldman, J. (2022). YouTube tests users’ tolerance for increased ad loads. EMARKETER. https://www.emarketer.com/content/catherine
Goldstein, D. G., Suri, S., McAfee, R. P., Ekstrand-Abueg, M., & Diaz, F. (2014). The economic and cognitive costs of annoying display advertisements. Journal of Marketing Research, 51(6), 742-752.
Guadagno, R. E., Rempala, D. M., Murphy, S., & Okdie, B. M. (2013). What makes a video go viral? An analysis of emotional contagion and Internet memes. Computers in human behavior, 29(6), 2312-2319.
Gutierrez, G. (2021). The welfare consequences of regulating Amazon. Job Market Paper, New York University.
Katz, M. L. (2019). Platform economics and antitrust enforcement: A little knowledge is a dangerous thing. Journal of Economics & Management Strategy, 28(1), 138-152.
Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. The American economic review, 75(3), 424-440.
Kemp, S. (2023). YouTube users, stats, data & trends. DataReportal – Global Digital Insights. https://datareportal.com/essential-youtube-stats#:~:text=379.7%20million%20users%20aged%2018,of%20YouTube's%20total%20ad%20audience
Knudsen, E. S., & Belik, I. (2023). The Achilles heel of interconnected user networks: Network firms and the vulnerability of rapid decline. Technological Forecasting & Social Change/Technological Forecasting and Social Change, 195, 122754.
Kumar, S. (2019). The algorithmic dance: YouTube's Adpocalypse and the gatekeeping of cultural content on digital platforms. Internet Policy Review, 8(2), 1-21.
Lan, S., Liu, K., & Dong, Y. (2019). Dancing with wolves: how value creation and value capture dynamics affect complementor participation in industry platforms. Industry and Innovation, 26(8), 943-963.

Lang, A., Dhillon, K., & Dong, Q. (1995). The effects of emotional arousal and valence on television viewers' cognitive capacity and memory. Journal of Broadcasting & Electronic Media, 39(3), 313-327.

Li, Z., & Wang, G. (2021). Regulating powerful platforms: Evidence from commission fee caps in on-demand services. Available at SSRN 3871514.

Maffei, A., Vencato, V., & Angrilli, A. (2015). Sex differences in emotional evaluation of film clips: interaction with five high arousal emotional categories. PloS one, 10(12), e0145562.

Marshall, A. (1890). Principles of economics.

McCarthy, R. V., McCarthy, M. M., Ceccucci, W., Halawi, L. (2022). Applying predictive analytics (pp. 89-121). Springer International Publishing.

McCoy, S., Everard, A., Polak, P., & Galletta, D. F. (2008). An experimental study of antecedents and consequences of online ad intrusiveness. Intl. Journal of Human–Computer Interaction, 24(7), 672-699.

Moore, J. F. (1993). Predators and prey: a new ecology of competition. Harvard business review, 71(3), 75-86.

Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. Management science, 51(10), 1494-1504.

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). Platform revolution: How networked markets are transforming the economy and how to make them work for you. WW Norton & Company.

Pittock, J. (2023). The history of YouTube advertising. Top Paid Media Experts for YouTube and Google Ads. https://yugomedia.co/history-of-youtube-advertising/

Post, E. L., & Sekharan, C. N. (2015). Comparative study and evaluation of online ad-blockers. In 2015 2nd International Conference on Information Science and Security (ICISS) (pp. 1-4). IEEE.

Puwandi, P. H., DE, G. T., & Brasali, N. (2020). The factors affecting consumer response towards online video advertisement: YouTube as a platform. International Journal of Multicultural and Multireligious Understanding, 7(2), 375-390.

Riedel, A., Mulcahy, R., Beatson, A., & Weeks, C. (2024). Advertising in Freemium Services: Lack of Control and Intrusion as the Price Consumers Pay. Journal of Advertising, 1-20.

Rietveld, J. (2017). Creating and capturing value from freemium business models: A demand‐side perspective. Strategic Entrepreneurship Journal, 12(2), 171-193.

Rietveld, J., Ploog, J. N., & Nieborg, D. B. (2020). THE COEVOLUTION OF PLATFORM DOMINANCE AND GOVERNANCE STRATEGIES: EFFECTS ON COMPLEMENTOR PERFORMANCE OUTCOMES. Academy of Management Discoveries.

Rietveld, J., & Schilling, M. A. (2020). Platform Competition: A systematic and interdisciplinary review of the literature. Journal of Management, 47(6), 1528–1563.

Rietveld, J., Schilling, M. A., & Bellavitis, C. (2019). Platform strategy: Managing ecosystem value through selective promotion of complements. Organization Science, 30(6), 1232-1251.

Ritala, P., Agouridas, V., Assimakopoulos, D., & Gies, O. (2013). Value creation and capture mechanisms in innovation ecosystems: a comparative case study. International Journal of Technology Management, 63(3/4), 244.

Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. Journal of the European economic association, 1(4), 990-1029.

Rysman, M. (2009). The economics of two-sided markets. Journal of economic perspectives, 23(3), 125-143.
Sabourin, V. (2016). Multi Sided Platforms (MSPs) Value Captation and Monetization Strategies: A Strategic Management Perspective. Business Management and Strategy, 7(1), 189-205.
Solomons, M. (2024). 90 YouTube Statistics: Revenue, marketing, and content. Linearity Blog.
Statista. (2024). Leading video content type worldwide Q4 2024, by usage reach. https://www.statista.com/statistics/1254810/top-video-content-type-by-global-reach/
Thatchenkery, S., & Katila, R. (2023). Innovation and profitability following antitrust intervention against a dominant platform: The wild, wild west?. Strategic Management Journal, 44(4), 943-976.
Zhu, F. (2018). Friends or foes? Examining platform owners' entry into complementors' spaces. Journal of Economics &Amp Management Strategy, 28(1), 23–28.
Zhu, F., & Liu, Q. (2018). Competing with complementors: An empirical look at Amazon. com. Strategic management journal, 39(10), 2618-2642.
Zuboff, S. (2023). The age of surveillance capitalism. In Social theory re-wired (pp. 203-213). Routledge.

7. Appendices

7.1 Appendix A

The cognitive interviews were conducted on a sample of 6 participants. The participants were asked to think out loud when answering questions and propose any adjustments that could improve the survey. Their feedback was directly implemented to improve question clarity, response options and survey flow. Additionally, to help determine the right ad load for the control and treatment group, 5 different versions of the video were used with varying ad loads: version 1 had an ad load of 15 seconds, version 2 had an ad load of 30 seconds, version 3 had an ad load of 60 seconds, version 4 had an ad load of 90 seconds, and version 5 had an ad load of 120 seconds. In versions 1, 2 and 3, participants experienced the chosen ad load as ‘average’, which seems to be in line with Goldman (2022). Version 4 had one participant choosing ‘slightly above average’, but a second participant with this version chose ‘average’ as well. The participant with version 5 chose ‘moderately above average’. To choose the most fitting version for the treatment and control group, the ad load for the treatment group needed to be noticeably increased for a significant portion of participants, but not to the point of being unrealistic as a value capture strategy. Based on this criteria, version 5 was picked for the treatment group to ensure enough participants would notice the treatment. Version 2 was picked for the control group (Goldman, 2022).

7.2 Appendix B

Thesis MOT

Survey Flow

Standard: Opening statement (1 Question)

Standard: Experiment notice (1 Question)

BlockRandomizer: 1 - Evenly Present Elements

EmbeddedData

condition = 1

EmbeddedData

condition = 0

Branch: New Branch

If

If condition Is Equal to 1

Standard: Experiment Treatment (2 Questions)

Branch: New Branch

If

If condition Is Equal to 0

BlockRandomizer: 1 - Evenly Present Elements

Standard: Experiment Control 1 (2 Questions)

Standard: Experiment Control 2 (2 Questions)

Standard: Experiment Control 3 (2 Questions)

Standard: Experiment Control 4 (2 Questions)

Branch: New Branch

If

If Please watch to the end (full screen option in the bottom right corner): After watching, you can... Is Displayed

EmbeddedData

Group = Treatment

Branch: New Branch

If

If Please watch to the end (full screen option in the bottom right corner): After watching, you can... Is Displayed

EmbeddedData

Group = Control 1

Branch: New Branch

If

If Please watch to the end (full screen option in the bottom right corner): After watching, you can... Is Displayed

EmbeddedData

Group = Control 2

Branch: New Branch

If

If Please watch to the end (full screen option in the bottom right corner): After watching, you can... Is Displayed

EmbeddedData

Group = Control 3

Branch: New Branch

If

If Please watch to the end (full screen option in the bottom right corner): After watching, you can... Is Displayed

EmbeddedData

Group = Control 4

Standard: AC (1 Question)

Standard: H2 & H3 (4 Questions)

Standard: H1 (2 Questions)

Standard: Post-experiment (5 Questions)

Standard: Control questions (9 Questions)

Block: Demographics (2 Questions)

Page Break

Start of Block: Opening statement

OS **Opening Statement** You are being invited to participate in a research study titled “How platform users react to value capturing strategies". This study is being done by Wies Biesbroeck from the TU Delft. The purpose of this research is to find out how platform users interact with a large platform, in this case **YouTube,** and will take you approximately 8 minutes to complete. The data will be used for a master thesis and might be used for publication later. To acquire all necessary data, you will need to watch a video no longer than 5 minutes and complete a closed answer survey containing 26 questions. **Please read the questions and statements carefully**. As with any online activity, the risk of a data breach is always possible. Your answers in this study will remain confidential to the best of our ability. We will minimize any risks by keeping the survey completely anonymous, so in case of a breach, data can't be traced back to participants. The only personal data required are your age and gender. **Your participation in this study is entirely voluntary and you can withdraw at any time.** You are free to omit any questions. Questions regarding the survey or data can be asked at w.w.biesbroeck@student.tudelft.nl By clicking through to the next page, you **automatically agree with this Opening Statement** and start the survey.

End of Block: Opening statement

Start of Block: Experiment notice

Notice **!Important!** On the following page, you will need to watch a video to complete the rest of the survey. **For the best result, please make sure you have good internet connection and watch the video carefully with sound!** The option to continue will appear after the video has finished.

End of Block: Experiment notice

Start of Block: Experiment Treatment

time_treatment Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Treatment Please watch to the end (full screen option in the bottom right corner):
After watching, you can continue with the survey

End of Block: Experiment Treatment

Start of Block: Experiment Control 1

time_control_1 Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Control 1 Please watch to the end (full screen option in the bottom right corner):
After watching, you can continue with the survey

End of Block: Experiment Control 1

Start of Block: Experiment Control 2

time_control_2 Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Control 2 Please watch to the end (full screen option in the bottom right corner):
After watching, you can continue with the survey

End of Block: Experiment Control 2

Start of Block: Experiment Control 3

time_control_3 Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Control 3 Please watch to the end (full screen option in the bottom right corner):
After watching, you can continue with the survey

End of Block: Experiment Control 3

Start of Block: Experiment Control 4

time_control_4 Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Control 4 Please watch to the end (full screen option in the bottom right corner):
After watching, you can continue with the survey

End of Block: Experiment Control 4

Start of Block: AC

ac1 Which of the following did you see in the video? Please select everything you saw.

- ☐ Coral (1)
- ☐ Penguïns (2)
- ☐ Icebergs (3)
- ☐ Sharks (4)
- ☐ Mangroves (5)

Octopuses (6)

Sea Lions (7)

Jellyfish (8)

End of Block: AC

Start of Block: H2 & H3

premium_use YouTube Premium is a paid membership that allows you to use YouTube without ads. Have you ever used YouTube Premium?

I have never heard of YouTube Premium (1)

I never had YouTube Premium (2)

I have used YouTube Premium in the past (3)

I am currently using YouTube Premium (4)

willingness_regular Given your regular experience with ads on YouTube, what is the maximum price you would be willing to pay for YouTube Premium per month?

€0 (1)

€2,50 (2)

€5 (3)

€7,50 (4)

€10 (5)

€12,50 (6)

◯ €15 (7)

◯ €17,50 (8)

◯ €20 (9)

◯ €22,50 (10)

◯ €25 (11)

◯ More than €25 (12)

likeliness_to_leave Imagine this scenario: From this moment, every video you watch on YouTube of similar length has the same number and duration of ads as in the video you just watched. YouTube Premium would also not be available. How likely would you be to take the following actions?

	Extremely unlikely (1)	Moderately unlikely (2)	Slightly unlikely (3)	Neutral (4)	Slightly likely (5)	Moderately likely (6)	Extremely likely (7)
Stop using YouTube (1)	◯	◯	◯	◯	◯	◯	◯
Lower my use of YouTube (2)	◯	◯	◯	◯	◯	◯	◯
Increase my use of YouTube (3)	◯	◯	◯	◯	◯	◯	◯

Switch to another platform (4)	○	○	○	○	○	○	○

willingness_scenario If YouTube Premium was available in this scenario, what is the maximum price you would be willing to pay for YouTube Premium per month?

○ €0 (1)

○ €2,50 (2)

○ €5 (3)

○ €7,50 (4)

○ €10 (5)

○ €12,50 (6)

○ €15 (7)

○ €17,50 (10)

○ €20 (11)

○ €22,50 (12)

○ €25 (13)

○ More than €25 (14)

End of Block: H2 & H3

Start of Block: H1

impact_enjoyment How did the ads impact your enjoyment of the video?

○ Extremely negative (1)

○ Moderately negative (2)

○ Slightly negative (3)

○ Neutral (4)

○ Slightly positive (5)

○ Moderately positive (6)

○ Extremely positive (7)

impact_magnitude Compared to how ads usually affect your enjoyment of videos, how did the ads impact your enjoyment of this video?

○ The ads in this video impacted my enjoyment extremely less than usual (1)

○ The ads in this video impacted my enjoyment moderately less than usual (2)

○ The ads in this video impacted my enjoyment slightly less than usual (3)

○ The ads in this video impacted my enjoyment the same as usual (4)

○ The ads in this video impacted my enjoyment slightly more than usual (5)

○ The ads in this video impacted my enjoyment moderately more than usual (6)

○ The ads in this video impacted my enjoyment extremely more than usual (7)

End of Block: H1

Start of Block: Post-experiment

video_opinion What is your opinion on the nature documentary in the video?

◯ I extremely disliked it (1)

◯ I moderatley disliked it (2)

◯ I slightly disliked it (3)

◯ Neutral (4)

◯ I slightly liked it (5)

◯ I moderately liked it (6)

◯ I extremely liked it (7)

content_interest How interested are you in the content category 'nature documentaries'?

◯ Extremely uninterested (1)

◯ Moderately uninterested (2)

◯ Slightly uninterested (3)

◯ Neutral (4)

◯ Slightly interested (5)

◯ Moderately interested (6)

◯ Extremely interested (7)

perceived_duration What do you think about the duration of ads in the video?

○ Extremely below average (1)

○ Moderately below average (2)

○ Slightly below average (3)

○ Average (4)

○ Slightly above average (5)

○ Moderately above average (6)

○ Extremely above average (7)

perceived_number What do you think about the number of ads in the video?

○ Extremely below average (1)

○ Moderately below average (2)

○ Slightly below average (3)

○ Average (4)

○ Slightly above average (5)

○ Moderately above average (6)

○ Extremely above average (7)

perceived_relevancy How relevant were the ads for you in the video?

○ They were extremely irrelevant (1)

○ They were moderately irrelevant (2)

○ They were slightly irrelevant (3)

○ Neutral (4)

○ They were slightly relevant (5)

○ They were moderately relevant (6)

○ They were extremely relevant (7)

End of Block: Post-experiment

Start of Block: Control questions

youtube_usage How many hours per day do you spend on YouTube, on average?

○ 0 hours (1)

○ 0 to 0.5 hour (2)

○ 0.5 to 1 hour (3)

○ 1 to 1.5 hours (4)

○ 1.5 to 2 hours (5)

○ 2 to 2.5 hours (6)

○ 2.5 to 3 hours (7)

○ 3+ hours (8)

content_usage What type of content do you mostly watch on YouTube? You can select multiple answers.

☐ Music videos (1)

☐ YouTube shorts (2)

☐ Comedy (3)

☐ Live streams (4)

☐ Educational entertainment (5)

☐ Tutorials (6)

☐ Sports (7)

☐ Product reviews (8)

☐ Influencers and Vlogs (9)

☐ Gaming (10)

☐ Study/work related (11)

☐ Other (12)

experience_premium What is your experience with YouTube Premium? Please leave unanswered if you never used YouTube Premium

○ Extremely bad (1)

○ Moderately bad (2)

○ Slightly bad (3)

○ Neutral (4)

○ Slightly good (5)

○ Moderately good (6)

○ Extremely good (7)

adblocker Are you using a functioning ad-blocker which allows you to never watch ads on YouTube?

○ No (1)

○ Yes (2)

ads_experience How do you typically feel about ads?

○ They are extremely annoying (1)

○ They are moderately annoying (2)

○ They are slightly annoying (3)

○ Neutral (4)

○ They are slightly amusing (5)

○ They are moderately amusing (6)

○ They are extremely amusing (7)

satisfaction_youtube How satisfied are you with YouTube as a content platform?

○ Extremely dissatisfied (1)

○ Moderately dissatisfied (2)

○ Slightly dissatisfied (3)

◯ Neutral (4)

◯ Slightly satisfied (5)

◯ Moderately satisfied (6)

◯ Extremely satisfied (7)

ac2 To help improve the quality of the data, please leave this question unanswered and continue with the next question.

◯ Extremely dissatisfied (1)

◯ Moderately dissatisfied (2)

◯ Slightly dissatisfied (3)

◯ Neutral (4)

◯ Slightly satisfied (5)

◯ Moderately satisfied (6)

◯ Extremely satisfied (7)

paid_subscriptions On which of the following platforms do you have a paid subscription, **which you are personally paying for**?

▢ Netflix (1)

▢ Prime Video (2)

▢ Disney+ (3)

▢ HBO Max (4)

- Apple TV (5)
- ESPN (6)
- Via Play (7)
- Videoland (8)
- Discovery Plus (9)
- Vimeo (10)
- Twitch (11)

device On what device do you usually watch YouTube videos?

- Phone (1)
- Tablet (2)
- PC or laptop (3)
- Smart TV (4)
- Other (5)

End of Block: Control questions

Start of Block: Demographics

gender What is your gender?

- Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

age What is your age?

○ 18 - 24 (1)

○ 25 - 34 (2)

○ 35 - 44 (3)

○ 45 - 54 (4)

○ 55 - 64 (5)

○ 65+ (6)

End of Block: Demographics

7.3 Appendix C

Title: The Hidden World of Islands

Creator: Natural World Facts

URL: https://www.youtube.com/watch?v=cUg70VLQZOQ&t=981s

Length: 3:21 (from 12:58 to 16:19)

Title: TOYOTA HILUX Commercial

Creator: Papaya Films

URL: https://www.youtube.com/watch?v=SUg1ourqwTI

Length: 0:30

Title: Taco Bell $7 Luxe Box | Ultimate Value Meal | Delicious TV Commercial #tvcommercials #tacobell

Creator: Tv Commercials

URL: https://www.youtube.com/watch?v=BKgRAwOi9SU

Length: 0:29 (from 0:04 to 0:33)

Title: YoungCapital - Make Money Work (reclame 2018)

Creator: YoungCapital

URL: https://www.youtube.com/watch?v=Zcc6QQC2Zrg

Length: 0:30

Title: #MillionNation - 1 Million & Lady Million | PACO RABANNE

Creator: Rabanne

URL: https://www.youtube.com/watch?v=COzVP0yQss8

Length: 0:31 (from 0:41 to 1:12)