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Marketing Mix Modelling for the Gaming Industry: Quantifying Influencer and Earned-Media Effects on Steam Wishlist Formation

Tesi di Laurea Magistrale in
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Abstract

This thesis investigates the marketing mix of an indie video game with a specific emphasis on influencer marketing, addressing the measurement challenge faced by small studios that operate with limited budgets and incomplete user-level tracking. The study's objective is to quantify the incremental contribution of major pre-launch channels to demand formation, using daily Steam wishlist additions ("Adds") as the key performance indicator, observed over a 160-day period. A time-series Marketing Mix Model (MMM) is developed using a log-linear regression framework in which daily Adds are explained by time-varying marketing exposures across five channels (YouTube, Twitch, Reddit, TikTok, and Press/Media). To reflect carryover dynamics, exposures are transformed using adstock, and the specification includes controls for a baseline time trend, day-of-week seasonality, and two high-impact product beats (demo release and playtest). Estimation relies on Newey–West (HAC) standard errors to account for autocorrelation and heteroskedasticity typical of daily marketing time series. Results from the aggregated MMM show positive and statistically significant elasticities for YouTube ($\beta \approx 0.09$), Twitch ($\beta \approx 0.10$), Reddit ($\beta \approx 0.10$), and Press/Media ($\beta \approx 0.12$), while TikTok exhibits a negative coefficient ($\beta \approx -0.09$) that is interpreted cautiously as likely reflecting timing and collinearity rather than a true negative causal effect. Modeled attribution highlights Press/Media and YouTube as the largest explained shares of incremental Adds. Product events dominate short-term dynamics: the demo release is associated with an approximately 7.5× multiplicative uplift versus baseline, and the playtest with roughly +33%. Model comparisons reveal the classic trade-off between granularity and robustness: an influencer-level decomposition substantially improves in-sample fit but fails to generalize (overfitting), whereas congruence-based segmentation models improve holdout performance. However, the congruence analysis finds no statistically significant differences in effectiveness between "fit" and "non-fit" influencer groups (indie-fit and genre-fit), suggesting that, within the gaming domain, broader influencer outreach can be as effective as niche-aligned targeting for wishlist conversion.

Keywords: Marketing mix modeling (MMM); influencer marketing; indie video games;

Steam wishlists; time-series regression; influencer–product congruence

Abstract in lingua italiana

Questa tesi analizza il marketing mix di un videogioco indie, con un focus specifico sul ruolo dell'influencer marketing, in un contesto in cui i budget sono limitati e la misurazione user-level è spesso impraticabile. L'obiettivo è stimare il contributo incrementale dei principali canali digitali nella fase pre-lancio, utilizzando come metrica di outcome le aggiunte giornaliere alla wishlist su Steam ("Adds"), osservate su un orizzonte di 160 giorni. La ricerca adotta un Marketing Mix Model (MMM) basato su regressione log-lineare su serie storiche, in cui le Adds sono spiegate da esposizioni time-varying su cinque canali (YouTube, Twitch, Reddit, TikTok e Press/Media), opportunamente trasformate tramite adstock per rappresentare effetti di carryover, e controllate per trend temporale, stagionalità settimanale e due eventi ad alto impatto (rilascio della demo e playtest). La stima utilizza errori standard Newey–West (HAC) per gestire autocorrelazione e eteroschedasticità. I risultati del modello aggregato indicano effetti positivi e significativi per YouTube ($\beta \approx 0{,}09$), Twitch ($\beta \approx 0{,}10$), Reddit ($\beta \approx 0{,}10$) e Press/Media ($\beta \approx 0{,}12$), mentre TikTok mostra un coefficiente negativo ($\beta \approx -0{,}09$), da interpretare con cautela. In termini di attribuzione modellata, Press/Media e YouTube rappresentano le quote maggiori dell'incremento spiegato. Inoltre, gli eventi prodotto risultano determinanti: il rilascio della demo genera un uplift moltiplicativo di circa $7{,}5\times$ rispetto al baseline, e il playtest un incremento di circa +33%. Confrontando specifiche alternative, la decomposizione "influencer-level" migliora il fit in-sample ma soffre di overfitting, mentre modelli che segmentano YouTube per congruenza influencer–prodotto migliorano la generalizzazione out-of-sample senza però evidenziare differenze statisticamente robuste tra influencer "fit" e "non-fit". Nel complesso, la tesi mostra la fattibilità di un MMM per campagne indie e propone indicazioni operative su allocazione canali e pianificazione di burst coordinati attorno a beat di prodotto.

Parole chiave: Marketing Mix Modeling (MMM); influencer marketing; videogiochi indie; wishlist di Steam; regressione su serie temporali; congruenza influencer-prodotto

Contents

1 | Introduction

Marketing effectiveness measurement has become increasingly challenging in digital markets, where consumer journeys span multiple platforms and where user-level tracking is constrained by privacy regulation and platform policies. In this environment, Marketing Mix Modeling (MMM) remains a relevant, privacy-safe approach to quantify how marketing activities contribute to business outcomes using aggregate time-series data.

This challenge is particularly strong in the indie video game industry. Indie studios operate with limited budgets, short and event-driven campaign windows, and strong dependence on earned media. Instead of relying primarily on large-scale paid advertising, many indie game campaigns attempt to generate awareness and credibility through influencer content, community discussion, and third-party media coverage. At the same time, these channels are difficult to measure and compare, because they are often observed through exposure proxies (views, mentions, articles) rather than standardized spend metrics.

Against this background, the objective of this thesis is to quantify the relative effectiveness of key influencer-driven and earned media channels within a single-game pre-launch campaign, using an MMM-inspired modeling framework. The core outcome metric is daily Steam wishlist additions (“Adds”), which represent observable pre-launch purchase intent. The empirical analysis models daily Adds over a 160-day period as a function of daily exposure levels across five channels: YouTube influencer videos, Twitch live streaming, Reddit discussions, TikTok short-form content, and online press/media coverage. To reflect typical marketing dynamics, the model incorporates log transformations and adstock effects, and controls for time trend, day-of-week seasonality, and major product events (the release of a public Demo and a Playtest period). In addition to a baseline aggregated model, the thesis compares alternative specifications that increase granularity, including a decomposed influencer-level model and theory-driven segmentation of YouTube exposures based on influencer–product congruence.

The thesis contributes to both marketing analytics and the gaming marketing literature in three ways. First, it provides an interpretable and replicable approach to integrate influencer and earned media exposure measures into an MMM-style time-series framework.

Second, it offers empirical evidence from an indie game case study, highlighting which channels and campaign elements are most associated with pre-launch demand. Third, it operationalizes influencer–product congruence (through "indie fit" and "genre fit") and evaluates whether congruence moderates the effectiveness of influencer exposure.

The remainder of the thesis is structured as follows. Chapter 2 reviews the theoretical background on MMM, influencer marketing mechanisms, and the indie game marketing context. Chapter 3 describes the research design, data sources, variable construction, and model specifications. Chapter 4 presents the empirical results, including model comparisons, channel-level effectiveness, the impact of high-impact events, and the congruence analysis, followed by discussion and managerial implications. Chapter 5 concludes by summarizing the main findings, outlining academic contributions, and proposing future research directions.

2 | Theoretical Background and Literature Review

2.1. Review Methodology

Scholarly research related to marketing mix modeling (MMM) remains relatively limited, particularly concerning its intersection with influencer marketing. The primary literature search was conducted across major academic databases, including Google Scholar, Elsevier's ScienceDirect, IEEE Xplore, Semantic Scholar, SpringerLink, and Scopus. The query implemented in Elsevier's advanced search was specifically constructed as follows: ("marketing mix model*") AND ("influencer marketing" OR "social media" OR "digital" OR "media" OR "advertisement"). This initial search yielded over 300 results.

These sources were further filtered to prioritize recent publications, particularly those from approximately 2018 onward, due to rapid advancements within influencer marketing and MMM methodologies. Additional relevant articles were identified using a snowballing approach, examining citations within selected papers to ensure comprehensive coverage of influential studies. Sources included empirical research, meta-analyses, and theoretical frameworks from reputable academic journals, such as the Journal of Marketing, Journal of Interactive Advertising, and Journal of the Academy of Marketing Science.

The thematic focus was strictly maintained on three core areas: (a) contemporary developments in MMM, particularly those utilizing advanced quantitative approaches such as Bayesian and machine learning techniques; (b) psychological and economic dimensions influencing the effectiveness of influencer marketing; and (c) marketing dynamics specific to indie video games. Sources not explicitly aligned with these themes were excluded to ensure clarity and relevance.

Throughout the review, attention was given to capturing the conceptual foundations and technical approaches central to MMM and influencer marketing effectiveness, as these elements constitute the theoretical and practical backbone of the research.

2.2. Marketing Mix Model (MMM)

Marketing Mix Modeling (MMM) serves as the quantitative foundation for evaluating how different marketing activities contribute to outcomes like sales or revenue. In essence, MMM is an analytical approach that applies statistical modeling to historical data in order to estimate the incremental impact of various marketing tactics on a key performance metric (such as game unit sales or revenue). By examining patterns of spend and response over time, MMM attempts to tease apart the contribution of each element of the marketing mix – for example, advertising on different channels, price promotions, or other marketing actions – to overall performance. This section provides a scholarly definition of MMM, discusses its significance and applications in both general marketing and the video game industry, and reviews recent methodological advancements that enhance MMM's relevance for modern, data-scarce contexts.

2.2.1. Definition and Relevance of MMM

In marketing scholarship, MMM is defined as a top-down econometric modeling technique that evaluates how marketing inputs relate to outputs at an aggregate level (Kannan et al., 2016; Liu, Steiner, & Aquino, 2014). Unlike user-level attribution methods that track individual consumers, MMM operates on aggregate time-series data (e.g., weekly or monthly totals), relating fluctuations in marketing activities to fluctuations in outcomes. Formally, MMM is often implemented as a regression-based model where the outcome (such as sales at time t) is regressed on various marketing spend variables (advertising spend in channel i at time t, etc.) and control variables like seasonality or economic factors. The regression coefficients (often denoted β) represent the estimated effect or elasticity of each marketing channel on sales. To improve realism, these models typically incorporate non-linear response curves and lagged effects: for instance, marketing science literature shows that advertising has diminishing returns (each additional dollar spent yields a smaller incremental sales lift at high spend levels) and carryover effects (ads may continue to drive some sales for weeks after the spend) (Cain, 2022; Köhler, Mantrala, Albers, & Kanuri, 2017).

Neil Borden's early concept of the marketing mix (the "4 Ps" of Product, Price, Place, Promotion) provided a conceptual starting point for thinking about how various marketing decisions drive outcomes. MMM evolved this idea by providing a quantitative, data-driven tool to measure the impact of especially the Promotion element (and other Ps as relevant) in real terms. Modern MMMs often treat marketing effects as incremental (above a baseline sales level that would occur with no marketing) and seek to approximate causal influence despite using correlational data, by carefully controlling for confounding factors and business cycles (Cain, 2022).

The relevance of MMM in today's marketing landscape has actually increased in recent years. With stricter digital privacy regulations (like the GDPR and Apple's App Tracking Transparency) limiting user-level tracking, many companies have turned back to MMM as a privacy-safe way to measure marketing effectiveness at the aggregate level. This has been described as an "MMM renaissance" in the digital advertising industry. For instance, Meta (Facebook) in 2021 released an open-source MMM library called Robyn, signaling a renewed industry investment in MMM techniques for budget allocation in a post-cookie world. Academically, MMM is now seen not just as a tool for big consumer goods firms, but as a broadly applicable approach for any context where marketers need to make budget decisions without granular tracking of users. This includes the video game sector: marketing scholars note that MMM provides a strategic, holistic view of what drives sales or engagement, which is valuable in fast-moving, multi-channel environments like gaming.

2.2.2. Applications of MMM in Marketing and Video Games

Historically, MMM has been heavily used by large advertisers (e.g., in consumer packaged goods and retail) to guide multi-million-dollar marketing budgets. It allows firms to quantify the return on investment (ROI) of each channel and to perform "what-if" analyses for rebalancing spend. For example, an MMM might reveal that for a given brand, television advertising is yielding a diminishing ROI beyond a certain spend level, suggesting that excess budget could be shifted to digital channels for better returns (Cain, 2022). In practice, companies use MMM results to identify the optimal budget allocation – often aiming to equalize the marginal ROI of each channel, thereby maximizing total effectiveness. Return on Ad Spend (ROAS) is a common metric derived from MMM: by comparing the estimated sales contribution of a channel to the spend, marketers gauge efficiency. A well-calibrated MMM can highlight when a channel becomes "saturated" (additional spend yields minimal incremental sales) so that budgets can be cut there and moved to unsaturated channels. In marketing literature, this is aligned with the goal of marketing optimization – ensuring each dollar is spent where it has the most impact.

The video game industry presents a unique and compelling application area for MMM. Video games, especially indie games, operate in digital marketplaces (like Steam for PC games, or mobile app stores) where an array of marketing activities – from online ads to platform promotions to influencer streams – can influence sales. The industry is characterized by:

- **Digital distribution and global reach:** Games are sold online globally, which means marketing impact can vary by region. Heliste (2019) emphasizes that a lack of granularity in MMM can be problematic in such scenarios – a single model at a global level might mask important regional differences. For instance, an MMM that averages marketing impact worldwide could overlook that a channel is very effective in North America but not in South America. Heliste's research on complex retail environments analogous to gaming suggests modeling at a more granular level (by game or by region) to get actionable insights.

- **Short product lifecycles and "blockbuster" dynamics:** Unlike consumer staples that sell year-round, games often have intense launch periods and then quickly taper off in sales (a spike at release followed by a "long tail" of lower sales). This nonlinear sales trajectory means marketing impact can be highly time-sensitive. Studies on video game launches show that pre-launch and launch-period marketing communications (including PR buzz and ads) critically shape the initial sales trajectory (Burmester, Becker, van Heerde, & Clement, 2015). MMM applied in this context needs to capture those rapid changes and the interplay of hype and word-of-mouth.

- **Experience good and community influence:** Games are experience goods – players cannot fully judge quality until after purchase or play, leading them to rely on information from others (reviews, streams, etc.). This means earned media (like influencer videos or community reviews) can have outsized effects on sales. Empirical research has found that social signals (e.g., user reviews or streaming activity) significantly affect digital game demand (Zhu & Zhang, 2010). MMMs for games, therefore, often include variables to represent these community or social influences, beyond traditional paid media (Chintagunta, Nair & Sukumar, 2009).

In summary, MMM's general significance in marketing – to provide an evidence-based allocation of marketing resources – is highly pertinent to the gaming industry. It offers a way to decipher which marketing levers truly drive an indie game's success in a noisy, competitive market. However, applying MMM to games also introduces challenges (discussed in Section 4) that require careful adaptation of the standard models.

2.2.3. Advances in MMM Methodology

Contemporary research in marketing analytics has pushed MMM techniques forward, addressing some classical limitations of simple regression-based models. Two notable advancements are the adoption of **Bayesian statistical methods** and the use of **hierarchical (multi-level) models** with informed priors. These innovations are particularly relevant for indie game marketing applications where data may be limited or volatile.

Traditional MMM using ordinary least squares (OLS) regression can struggle when data are sparse or highly collinear (e.g., when multiple channels are active simultaneously). For an indie game with only a few months of sales history, an OLS regression might produce unstable or nonsensical estimates (such as negative advertising coefficients due to multicollinearity or overfitting). To combat this, Jin et al. (2017) proposed a Bayesian MMM framework that incorporates prior knowledge into the modeling process. In a Bayesian MMM, instead of estimating each channel's effect purely from limited data, the model is initialized with prior distributions for parameters – these could be informed by historical benchmarks or expert judgment (e.g., "online ads typically have a sales elasticity around 0.2, give or take"). The Bayesian model then updates these priors with the actual data, effectively "borrowing strength" when data are weak. This yields more stable estimates and guards against overfitting, as demonstrated by Jin et al. with Google's advertising data. For instance, in the indie game context, one could use prior knowledge like "strategy games on PC usually see a 2.5x return on ad spend for social media ads" as a prior for an MMM coefficient. The model would then adjust that belief based on the game's actual results, rather than estimating from scratch with few data points.

Another advancement is the use of **hierarchical models** (also known as multi-level models) which allow MMM to account for structured differences across products, regions, or segments. In a hierarchical Bayesian MMM, data from multiple games or markets can be modeled together, with higher-level distributions linking them. This is useful if an indie studio has several titles or if data from analogous products can inform the model. For example, Heliste (2019) suggests that analyzing at the individual game level (rather than lumping all products together) provides more accurate insights. A hierarchical approach lets each game have its own marketing effect estimates while sharing information about common patterns. Recent work by Chen et al. (2021) even adds constraints (like requiring that ad spend can't have a negative true effect on sales) to improve realism in MMM estimates. These techniques improve MMM's reliability, especially under the data constraints typical of indie games (limited history, one-time launch events, etc.).

In addition, modern MMM implementations increasingly use machine learning algorithms (ridge regression, decision trees, etc.) to capture complex non-linearities and interactions. These approaches can be useful to capture non-linearities and interaction effects that are difficult to represent in standard regression-based MMM. At the same time, they can be less transparent and may require more data to avoid overfitting. For these reasons, this thesis does not implement machine learning-based MMM as part of the empirical analysis, but considers it as a relevant "state of the art" direction for future research once richer datasets (e.g., longer time horizons or multiple comparable campaigns) are available.

In summary, the academic shift toward Bayesian, hierarchical, and machine learning-based MMM approaches highlights important directions for improving stability and realism, especially in data-scarce settings. However, these advanced methods typically require stronger data availability, stronger modeling assumptions, or additional implementation complexity. For this thesis, the empirical analysis follows a more classical MMM-inspired framework based on a log-linear time-series regression with adstock-transformed exposure variables, control variables for seasonality and events, and robust inference using HAC (Newey–West) standard errors. The advanced MMM approaches discussed above are therefore used primarily to motivate the methodological context and to position potential future extensions, rather than as techniques directly implemented in the empirical models presented in Chapter 3.

2.3. Influencer Marketing within MMM

Influencer marketing has emerged as a central component of many companies' promotion strategies in the social media age. It refers to the practice of leveraging individuals who have amassed an audience (social media influencers) to promote products in a more personal or relatable way than traditional advertising. This section examines influencer marketing from a theoretical perspective and how it can be integrated into a Marketing Mix Model.

2.3.1. Influencer Marketing: Definition and Relevance

Influencer marketing is defined in the literature as a strategy in which firms identify and engage key individuals who have influence over target consumers to endorse or promote offerings. In contrast to celebrity endorsements of the past, these influencers are often "regular" content creators who built their followings through social media platforms by producing content and interacting with followers (Campbell & Farrell, 2020). For example, Leung et al. (2022) define influencer marketing as a process where companies "enlist influencers to promote products and facilitate consumer decision-making," highlighting the deliberate engagement of influencers by brands. Campbell and Farrell (2020) similarly describe it as the practice of compensating or incentivizing individuals to create social media content about a product or service. In essence, the influencer serves as a mediator between the brand and consumers, providing a seemingly authentic voice that can sway consumer attitudes and behaviors.

In recent years, influencer marketing has become one of the fastest-growing segments of marketing. Brands across industries allocate substantial and increasing budgets to influencer campaigns. Surveys indicate that more than 75% of brands intent to dedicate influencer marketing budgets and over 80% of firms (in the U.S.) utilize influencers as part of their marketing mix (Leung et al., 2022). Industry estimates global influencer marketing spending at around $16 billion in 2022, rising to roughly $24 billion by 2024 – a reflection of rapid growth as marketers see returns from this channel (Beichert et al., 2024).

The academic research corroborates this effectiveness: a comprehensive meta-analysis by Pan et al. (2024), aggregating 1,531 effect sizes from 251 studies, found that influencer marketing has a significant impact on both non-transactional outcomes (like brand attitudes, engagement, and word-of-mouth intentions) and transactional outcomes (like purchase intentions and actual sales). Pan et al.'s analysis also delves into why influencer content works, pointing out that influencers can provide informational value (educating consumers) and emotional or hedonic value, and that their effectiveness is partly mediated by factors like source credibility and the audience's identification with the influencer.

Influencer marketing is especially pertinent to digital products and experience goods (like video games) because these products benefit greatly from peer-like recommendations and demonstrations. A Twitch streamer or YouTuber playing an indie game is effectively showcasing the product and providing social proof to viewers. Unlike a static ad, an influencer's gameplay video serves as both entertainment and a product trial for the audience. This can build hype and trust in a way traditional ads cannot. As Pan et al. (2024) note broadly, influencer promotions significantly shape consumer decision-making by leveraging trust and relatability. In the indie game arena, where big advertising budgets are rare, influencers often fill the gap – they generate awareness and credibility for new games in enthusiast communities. Indeed, influencer content frequently functions as "product demonstration, social proof, and community engagement" all at once for video games. It is therefore not surprising that many indie game successes (from Minecraft in its early days to breakout hits like Among Us) have been attributed in large part to exposure through influential content creators (the "Let's Play" videos, streaming sessions, etc.). This strategic importance of influencer marketing sets the stage for examining the nuances of different influencer types and how congruence and economic considerations moderate their effectiveness.

2.3.2. Definitions and Types of Influencers

Not all influencers are alike; both academics and practitioners classify influencers into **tiers** based on the size of their following, which often correlates with the nature of their influence. A widely cited taxonomy breaks them into nano-, micro-, macro- and mega-influencers, roughly in increasing order of audience size (Campbell & Farrell, 2020). It is important to note that exact follower count thresholds can vary by source, but the general distinctions are as follows:

Nano-Influencers

Nano-influencers are individuals with a relatively small follower base, often quoted as fewer than 5,000–10,000 followers on a given platform. They are typically ordinary users or niche content creators who have a tight-knit and highly engaged community. What nanos lack in reach, they make up for in intimacy and authenticity. Their audience often knows them personally or feels a close connection, which can translate to very high engagement rates – studies have observed that nano-influencers "often generate the highest engagement rates of all influencer categories" due to the strong trust and bond within their communities. Nano-influencers usually operate at low cost; many are willing to promote brands in exchange for free products or modest fees, given they are just starting out or do it as a passion. For indie game marketers, nano-influencers might include small-scale Twitch streamers or YouTubers who only have a few thousand subscribers but whose streams are frequented by dedicated fans. These fans are likely to value the nano-influencer's opinions highly, making any game recommendation feel like a personal suggestion from a friend. The trade-off is that a single nano-influencer can only drive a small number of sales due to limited reach. However, as discussed in Section 3.4, the ROI (return on investment) on nanos can be remarkably high – some research suggests that, per dollar spent, nanos outperform larger influencers in generating sales.

Micro-Influencers

Micro-influencers are often defined as those having on the order of 10,000 to 100,000 followers (Leung et al., 2022). They have built a moderate-sized audience, usually around a particular niche or interest area. Micros represent a middle ground: their follower count implies a broader reach than nanos, but they often retain a significant level of personal engagement and perceived authenticity. Many micro-influencers are seen as relatable experts in their domain – for example, a YouTuber with 50,000 subscribers who reviews indie games might be considered a micro-influencer. Their recommendations are often perceived as more credible and genuine than those of macro or mega influencers, who sometimes are viewed as having “sold out” due to frequent sponsorships. Research indicates that micro-influencers can command strong influence because their audiences are tightly focused and loyal, and their content feels less commercial. For indie game marketing, a partnership with several micro-influencers (each catering to a specific genre community, for instance) can yield a compound effect: each micro brings the game to a relevant niche audience with a message that feels tailored and trustworthy. Micros generally charge more than nanos (some make a living from content creation) but are still relatively cost-effective compared to macro/mega celebrities. They often strike a good balance between reach and engagement, which is why marketing literature and practice frequently highlight micro-influencers as valuable for campaigns needing credible word-of-mouth at scale (albeit smaller scale than mega reach).

Macro-Influencers

Macro-influencers typically have large followings in the range of hundreds of thousands (100,000 up to ~1 million). These are often professional content creators or minor celebrities in the social media space. By the time an influencer reaches macro status, their community is expansive and their content production is often more polished and frequent. Macro-influencers offer broad reach – a single post or video can expose a product to a vast audience quickly. However, the nature of their influence tends to be more one-to-many and less personal. Engagement rate (as a percentage of followers) often declines at this scale, because audiences are more heterogeneous and individual followers feel less personally connected to the influencer. Nonetheless, macros are powerful for creating mass awareness and are commonly used for product launches or when a brand wants to quickly build recognition. In the context of video games, a macro-influencer might be a well-known Twitch streamer or YouTube gamer with, say, 500,000 followers who, when they play a new indie game, can generate thousands of viewers and significant buzz. The effectiveness per viewer might be lower than that of a micro (since not all viewers are the “right” audience or as trusting), but the sheer volume can drive a substantial absolute number of sales or wish-list additions. Campbell & Farrell (2020) note that macro-level influencers often assume the role of professional endorsers – their persona and credibility as an entertainer become part of the value they offer to brands. Marketers must be cautious that as influencers get larger, audiences may have higher persuasion knowledge (awareness of the sponsored nature of content), which can make the endorsements feel more like traditional ads unless the influencer is highly selective in brand partnerships (Chen et al., 2023).

Mega-Influencers

Mega-influencers are those with follower counts in the millions – this category includes top-tier social media personalities and traditional celebrities who have moved onto platforms like Instagram, YouTube, or Twitch. Mega-influencers (and celebrities) provide massive reach and can single-handedly popularize a product within mainstream circles. However, by this stage, the influencer's relationship with followers is more akin to a media channel than a community friend. Engagement rates by percentage are typically the lowest among all influencer tiers, and content is often heavily commercialized or managed by teams. For an indie game, getting a mega-influencer or famous streamer to cover the game could result in a huge short-term spike in attention – potentially tens of thousands of concurrent viewers and widespread visibility. Yet, the conversion of those viewers into actual players may be uncertain and can depend on factors like the game's fit with the influencer's usual content (congruence) and the perceived authenticity of the endorsement. Also, mega-influencers are expensive – they might charge significant sums for a sponsored stream or video, often out of reach for indie marketing budgets. The literature observes a kind of inverse ROI relationship with influencer size: as influencer size goes up, the cost goes up and the engagement per follower tends to go down (Beichert et al., 2024). Beichert et al. (2023) empirically demonstrated this paradox – in their analysis, campaigns focusing on a network of smaller influencers yielded higher ROI than those investing heavily in a single mega-influencer. The reason, as they explain, is that as an audience grows into the millions, the tie strength between the influencer and any individual follower weakens; recommendations feel less personal, more people in the audience are outside the tight-knit interest group, and thus the persuasive power per person diminishes.

In summary, no single influencer type is universally "best" – each tier has advantages and trade-offs. The academic consensus is that marketers should choose influencer tiers based on campaign goals and target audience characteristics. For a niche indie game seeking credibility among core gamers, a cluster of nano/micro-influencers might be ideal. For a broad-appeal game trying to break into the mainstream, a macro/mega influencer might achieve the needed awareness. Often a portfolio approach is suggested, mixing tiers to combine reach and engagement, a concept supported by recent studies (e.g., Gu et al., 2024, on multi-influencer portfolio effects).

2.3.3. Influencer–Brand Congruence

A crucial factor that modulates the effectiveness of influencer marketing is congruence, often called influencer–brand fit or influencer–product fit. Influencer congruence refers to the perceived alignment or “fit” between the influencer and the product/brand they are promoting. This concept can be multi-faceted:

- **Influencer–Product Congruence:** How well the influencer’s typical content, image, or expertise matches the product category. (E.g., a gaming influencer promoting a video game has high product congruence, whereas the same influencer promoting an unrelated fashion accessory might have low congruence.)

- **Influencer–Audience Congruence:** The alignment between the influencer’s characteristics or values and those of their followers (the target consumers). This ties into how relatable the influencer is to their audience’s identity.

- **Influencer–Brand Congruence:** How well the influencer’s persona and style mesh with the brand’s overall image and values (Pan et al., 2024).

Theoretical grounding for why congruence matters comes from classic persuasion theories like the Match-up Hypothesis and self-congruity theory. In essence, when an endorsement “makes sense” – the influencer naturally fits the product – audiences are more likely to accept the message and not question the influencer’s motives. A highly congruent pairing boosts the influencer’s source credibility, as viewers perceive the influencer to have genuine expertise or authentic interest in the product. Additionally, high congruence means viewers experience less persuasion knowledge activation (they are less likely to think the influencer is just doing it for money) and thus less defensive resistance to the message.

Empirical research strongly supports the importance of congruence. Pan et al. (2024)’s meta-analysis found that influencer–brand fit is positively associated with consumer attitudes toward the brand and purchase intentions. In other words, better fit consistently led to better outcomes. Other studies reinforce specific aspects: for instance, Chen et al. (2023) report that congruence between an influencer and their audience’s interests or identity is “imperative” for maximizing impact – consumers prefer influencers they identify with, which enhances persuasiveness. When followers see themselves in the influencer (sharing demographics, values, or style), they form a stronger bond and the influencer’s recommendations carry more weight. This aligns with the idea of wishful identification, where followers aspire to be like the influencer; Koay et al. (2023) note that such identification can lead to impulse buying as consumers purchase products to emulate their admired influencer.

Influencer–product congruence has also been shown to affect perceived authenticity and trust. A study by Ju & Lou (2022) demonstrated that when an influencer is strongly associated with the type of product they endorse (say, a tech YouTuber promoting a new gaming laptop), audiences find the endorsement more credible and effective. Interestingly, Ju & Lou also found that the importance of congruence can be moderated by the nature of the influencer–follower relationship: if followers feel a very close, friendship-like bond with the influencer (what researchers call a communal relationship), they might support the influencer's promotion out of loyalty even if the product is not a perfect thematic fit. This suggests that while high congruence is generally the safest route to positive outcomes, some highly charismatic influencers with devoted communities can still drive success with slightly incongruent products due to goodwill.

In the gaming context, congruence is particularly salient. Gamers are diverse, and influencer audiences often coalesce around game genres and subcultures. A streamer known for horror games will have credibility when introducing a new horror indie title, but might face skepticism if they suddenly promote a children's mobile game (a mismatch). Here we see genre congruence as critical – aligning game genre with the influencer's usual domain. Another aspect is platform congruence: an influencer primarily on Twitch might have a community that expects live, unscripted gameplay content, whereas YouTube audiences might favor edited, informational videos. The fit between the game promotion format and the platform's norms can influence effectiveness. Additionally, since gaming communities are strongly tied to identity (people often label themselves as fans of certain game series or genres), an influencer who shares that identity with their followers can be very persuasive. In fact, Pan et al. (2024) found that a follower's social identity (e.g., identifying as a "gamer" or a member of a certain fan community) is a strong correlate of how they respond to influencer content. This implies that in indie game marketing, choosing influencers who are genuinely embedded in the relevant gamer community (and thus congruent with the audience) can yield better engagement and conversion.

Overall, high influencer–brand/product congruence tends to enhance marketing effectiveness: it leads to more positive attitudes, greater trust, and often measurable lifts in conversions (Ju & Lou, 2022). Low congruence, on the other hand, can backfire — audiences may perceive the sponsorship as inauthentic or purely mercenary, which can trigger skepticism or even backlash. Therefore, congruence is a key consideration in selecting influencers for a campaign, and in modeling terms, it suggests that the effectiveness coefficient of an influencer in an MMM could be moderated by congruence-related factors. Some advanced studies have started to include such moderating variables (e.g., an interaction term for congruence level) when evaluating influencer campaign performance.

Beyond congruence, scholars have examined other psychological mechanisms in influencer marketing that are worth noting. One is parasocial interaction (PSI) – the one-sided "friendship" that viewers feel toward an influencer or media personality. Lou & Kim

(2019) and Du et al. (2023) found that strong PSI can reduce audience resistance to persuasion. Essentially, if viewers feel like the influencer is their friend, they are less likely to react negatively to a sponsored post; they trust that recommendation more. This is related to congruence in that a congruent influencer likely has higher PSI with the audience to begin with. Another mechanism is the "image transfer" effect, described by Haq & Chiu (2024): the positive attributes of an influencer (coolness, expertise, etc.) can transfer onto the endorsed product in the minds of consumers. For example, if an indie game is promoted by an influencer known for high skill and authenticity, viewers might unconsciously attribute those qualities to the game itself. These psychological effects reinforce why having the right influencer (one who fits the brand and has built trust) is essential.

2.3.4. Economic Implications of Influencer Marketing

From a marketing economics perspective, a key question is how influencer marketing contributes to the bottom line and how to measure its return on investment (ROI). Unlike traditional advertising where exposures and outcomes are more directly quantified, influencer marketing can have both direct and indirect effects on sales.

A fundamental issue is understanding whether influencer campaigns create incremental demand or just shift demand around. Influencer marketing can work in several ways economically:

- It can generate new demand by reaching consumers who would not have purchased otherwise (acquisition effect).

- It can accelerate demand, causing people to buy sooner than they might have (perhaps moving up purchases, which is important around game launch timing).

- It can reallocate demand from competitors, meaning the influencer convinces consumers to buy one game over another.

Each of these has implications for how we measure ROI. If an influencer mainly accelerates existing demand (e.g., fans who would have bought the game eventually but did so on day one after seeing a streamer), the short-term sales bump might overstate the true incremental value. Conversely, if an influencer draws completely new players into the market, that is pure incremental revenue attributable to the campaign.

Beichert et al. (2023) approach influencer marketing as a revenue-generating instrument within the broader marketing mix, examining it in a data-driven way to see how much sales lift it produces relative to its cost. Their large-scale analysis (including millions of consumer observations) concluded that influencer marketing can indeed drive significant sales and that its ROI can be benchmarked alongside other channels. One of their notable findings, as mentioned earlier, is that smaller influencers often yield higher ROI than larger ones. In practical terms, if a company spends $10,000 on dozens of nano- and micro-influencers versus the same $10,000 on one or two mega-influencers, the former strategy tended to produce more sales per dollar in their study. The reasoning is tied to the concept of social capital: smaller influencers have a high concentration of social capital and trust with their audience, so their endorsements convert at a higher rate (Ren et al., 2023). Large influencers broadcast to many who are indifferent, so conversion rates are lower and thus cost per conversion higher.

This finding has strategic budgeting implications. For indie game marketers with tight budgets, it may be economically wiser to spread the budget across many micro-influencers who speak to various niche communities, rather than putting all funds into one big name. The result could be a more resilient campaign (not reliant on one person) and better overall ROI. In fact, Gu et al. (2024) emphasize managing an influencer campaign as a portfolio: the mix of influencer types (small vs large, broad vs niche) can be optimized for both reach and conversion efficiency. They find that combinations of influencers can have complementary effects on sales outcomes, which suggests marketers should not view "influencer marketing" as a monolithic spend but rather decide the optimal influencer mix.

Another economic aspect is measurement – what metrics to track for influencer performance. Academic literature cautions against relying solely on surface-level metrics like likes or views, as these don't always correlate with sales. Pan et al. (2024) differentiate between non-transactional outcomes (engagement, brand awareness) and transactional outcomes (purchases), noting that influencer marketing can be very effective at the former, but the latter is the ultimate goal for ROI. Thus, companies should identify which stage of the funnel they want to impact. For example, an indie game might use influencers to drive awareness and wishlist adds (upper-funnel metrics), which indirectly lead to sales at launch. If those are the objectives, the ROI might be seen in terms of cost per wishlist addition rather than immediate sales.

Several studies also highlight the role of disclosure and audience skepticism in moderating economic outcomes. If an influencer clearly discloses a sponsorship, does it hurt outcomes? Some evidence (e.g., De Cicco et al., 2021) indicates that when congruence is high, disclosure doesn't significantly harm persuasion – the fit and credibility can compensate. But if congruence is low, disclosure might amplify skepticism. This ties into ROI because highly skeptical audiences yield fewer conversions. Thus, achieving a good fit and authentic tone can actually improve the cost-effectiveness of an influencer campaign by minimizing wasted impressions on people who are turned off by a salesy vibe.

For indie developers, measuring ROI might extend beyond just sales. Influencer campaigns can have spillover benefits like driving players to try a free demo, increasing community size (e.g., Discord members), or generating user-generated content. All these can indirectly boost revenue or reduce future marketing costs. The literature suggests employing a funnel approach to influencer ROI: measure top-of-funnel effects (awareness, interest), mid-funnel (engagement, trial), and bottom-funnel (purchase, retention). If an influencer campaign is not immediately increasing sales, it may still be valuable if it's filling the funnel with future customers. This comprehensive view is important when integrating influencer marketing into MMM, as discussed next.

2.3.5. Influencer Marketing and MMM

Integrating influencer marketing into a Marketing Mix Model presents both theoretical and practical challenges. Influencer marketing can be thought of as another media channel or marketing input in the MMM framework, but it has distinctive features that require careful treatment. The goal is to incorporate influencer activity as a variable (or set of variables) in the model so that its contribution to sales can be quantified alongside other channels like advertising, price promotions, etc.

Conceptual integration: The simplest approach is to include an "influencer marketing" variable in the regression, analogous to other marketing spends. This could be measured in two primary ways:

- **Spend-based:** Use the amount of money spent on influencer partnerships per time period (e.g., total sponsorship fees paid to influencers each week).

- **Exposure-based:** Use the audience exposure generated by influencers, such as the number of influencer video views, hours of content streamed, or engagements generated by influencers about the product.

Each approach has pros and cons. A spend-based approach is straightforward and ties directly to budget. However, dollars spent may not translate linearly to consumer impressions because an influencer post could either flop or go viral beyond expectations. An exposure-based metric (like total views of sponsored content) might better capture the actual "marketing pressure" exerted on the audience. Kisilevich (2022) argues that for digital channels where reach isn't strictly proportional to spend, using impressions/views as the MMM input can improve accuracy. For example, a $500 payment to an influencer might yield 100,000 views in one campaign and only 10,000 in another; an MMM using spend alone would ignore this difference, whereas using views would account for it.

Influencer marketing is less schedule-able and more stochastic than typical ad channels. Influencer content can produce delayed effects: a YouTube video might keep attracting viewers (and driving sales) weeks or months after it's posted. This introduces carryover (lagged effects) that MMM must capture. It's advisable to include lagged terms or use an adstock transformation on the influencer variable to model the decay of influencer-driven interest over time. There is also the issue of saturation – viewers may see diminishing returns if they've watched multiple influencer videos about the same game (the first exposure has big impact, subsequent ones less so), aligning with the usual advertising saturation curve.

Another challenge is endogeneity and omitted variables. Influencer activity isn't always under the firm's control. Sometimes a game might go viral organically, with dozens of influencers picking it up spontaneously (as happened with games like Among Us). If we only track paid influencer campaigns, we might miss this "organic influencer" effect. The literature suggests treating organic influencer buzz as a separate variable or control. For example, one could include a variable for the volume of unpaid influencer mentions or community streams per week. This acts similarly to a media coverage or word-of-mouth variable. By accounting for it, the MMM can distinguish between sales driven by the marketer's own influencer program versus those emergent from the community. If such organic factors are omitted, the model might wrongly attribute their effect to other marketing inputs (omitted variable bias).

There is also a reverse-causality concern: successful games attract more influencer attention. If not properly modeled, one might incorrectly conclude that influencer videos caused sales, when high sales (or hype) actually caused more influencers to cover the game. Addressing this might involve using instruments or proxies (for example, lagging the influencer variable, or using only scheduled influencer content where timing is predetermined, or controlling for prior sales trends).

As discussed in Section 2.3, indie game datasets for MMM are often limited, and influencer marketing adds further volatility due to sharp spikes generated by a small number of creators. In the broader literature, Bayesian MMM with informative priors and hierarchical modeling are frequently proposed as solutions for stabilizing estimates under such constraints. In this thesis, these techniques are discussed as relevant methodological options; nevertheless, the empirical models are estimated using OLS within a transparent log-linear specification, combined with adstock transformations and robust Newey–West standard errors. This choice supports interpretability and replicability in a single-game case study context, while still capturing key MMM dynamics such as carryover and diminishing returns.

In summary, integrating influencer marketing into MMM involves carefully defining the influencer variables, accounting for their unique dynamics (carryover, saturation, organic vs paid), and possibly employing advanced modeling (Bayesian or interaction modeling) to handle the complexities. This integration is on the frontier of current practice – it is a timely research area since many firms are trying to quantify influencer ROI in the same analytical framework as other channels. The next section will discuss how these concepts apply specifically to the indie game industry, which in many ways provides an ideal testing ground for combining MMM and influencer marketing due to its reliance on digital buzz and the challenges of small data.

2.4. Indie Gaming Industry and MMM

Having reviewed the foundations of MMM and influencer marketing, we now turn to their intersection in the context of the gaming industry, with a particular focus on independent ("indie") video games. The indie game sector is a distinct environment that presents both challenges and opportunities for marketing analytics. This section (4) discusses the characteristics of indie game marketing (4.1), the adaptations needed to make MMM work for indie studios (4.2), and the central role of influencer marketing as part of the indie game marketing mix (4.3). Throughout, we highlight insights from academic studies and industry observations that illuminate how MMM can be applied to gaming, and what pitfalls or adjustments must be considered.

2.4.1. Indie Video Game Marketing Characteristics

The indie video game market is characterized by high competition and visibility challenges despite low distribution costs. Every year, thousands of new games are self-published or launched on platforms like Steam, itch.io, or the App Store, leading to what has been termed a "discovery crisis" in the industry. The primary hurdle for indie developers is not making a game (production) but getting it noticed by players amidst a flood of alternatives. Traditional advertising channels (TV commercials, print ads) are usually cost-prohibitive and inefficient for small studios, so indie marketing leans heavily on digital channels and platform ecosystems.

Another feature of this market is the "hype cycle" of game launches. Game sales tend to concentrate in a short window around release: a blockbuster-like spike during launch (especially if the game builds pre-release wishlists and hype), followed by a rapid drop and then a longer tail of smaller sales. Unlike products with steady year-round sales, games often live or die by their launch momentum. This means marketing impact is hugely time-sensitive – a well-timed campaign can make a launch, whereas a missed opportunity can't easily be recovered later. Post-launch, revenue trickles in through occasional spikes driven by updates, downloadable content (DLC), or discount promotions. From an MMM perspective, this temporal concentration violates some typical assumptions (like having enough steady data over time), requiring careful modeling (e.g., higher frequency data around launch, or piecewise modeling of launch vs. post-launch periods).

Moreover, digital distribution and near-zero marginal costs per unit sold mean that once a game is created, selling additional copies is almost pure profit. This makes marketing particularly crucial – with no physical production or distribution limiting sales, the bottleneck is entirely demand. Thus, for an indie game, effective marketing can have an outsized effect on total revenue relative to the development cost. In economic terms, indie game success often follows a winner-takes-all distribution: a few games explode in popularity (often due to successful marketing or viral reception), while the majority languish in obscurity. Small studios therefore have high leverage but also high risk in their marketing decisions.

Finally, community and word-of-mouth are integral to the gaming industry. Game communities (forums, Discord servers, social media groups) can create grassroots momentum. A game that captures the attention of a niche community can snowball into widespread success if it breaks out to influencers and media. On the flip side, a negative early reception (bad reviews or poor first impressions on streams) can doom an indie title. This amplifies the importance of earned media and influencer reactions, which often outweigh paid advertising in this sector. For these reasons, the gaming industry is a fertile ground for applying MMM in innovative ways, but it demands sensitivity to dynamics that are less pronounced in other industries.

2.4.2. Adapting MMM to Indie Game Marketing

Applying MMM to indie games requires adapting to data limitations and the unique mix of marketing channels. One major challenge is the paucity of historical data for a new game or small studio. A typical MMM for a big brand might use 2-3 years of weekly data (100+ data points) to estimate stable models. In contrast, an indie game might have only a few months of meaningful data, especially if the analysis focuses on the launch window. This is where the earlier discussed Bayesian MMM approaches become invaluable. By inputting prior knowledge (for example, how similar games performed on certain channels), an indie developer can run an MMM even with limited observations, with the priors guiding the model to reasonable estimates. Jin et al. (2017)'s Bayesian MMM framework is directly applicable here, as it was designed to stabilize marketing mix estimates in data-scarce environments.

Another adaptation is increased granularity in modeling. Heliste (2019) argued that for complex markets, one must model at a granular level to get actionable insights. For indie games, this could mean modeling each platform separately (PC vs. console vs. mobile) or each major region separately, rather than combining them. The reason is that marketing effectiveness can differ widely across platforms – for example, a YouTube campaign might drive a lot of Steam (PC) sales but have almost no effect on Nintendo Switch sales, if the Switch audience isn't watching YouTube on their consoles. A coarse model might attribute low average effectiveness to YouTube, whereas a granular model would reveal it's highly effective for one platform and irrelevant for another. Given indie budgets are limited, such insights (spend on what actually moves the needle per platform) are crucial.

Control for external events: Indie game sales are heavily influenced by platform-driven events and organic buzz. For instance, getting featured on the Steam homepage or a major gaming news outlet can cause a spike in sales without any marketing spend. An MMM for an indie game should include binary or continuous variables to capture these non-marketing shocks – e.g., a variable for "Steam Front Page Feature" in a given week. Including these ensures that a sudden sales jump from such an event is not mistakenly credited to, say, a concurrent ad campaign. Similarly, variables tracking social media trends (like a viral Reddit post or trending hashtag about the game) can improve the model. While such events are not marketing mix elements controlled by the firm, they form part of the environment in which the marketing operates and thus must be accounted for to isolate the true effect of the firm's actions.

Multiple objectives and KPIs: Indie games often have multiple key performance indicators beyond just sales. Wishlists (players expressing interest before launch), player retention, community size, and engagement metrics are important indicators of a game's health. A traditional MMM that only looks at sales might miss these nuances. An advanced approach could model multiple outcomes or incorporate these metrics as leading indicators. For example, one could first model what drives Steam wishlist additions (influencer coverage is often a big factor here), and then how wishlists convert to day-one sales. This goes beyond the classic MMM, edging into multi-equation models or structural models, but the principle is to tailor the modeling to what "success" means for the indie game in question.

Validation and case evidence: There have been a few academic and industry case studies applying MMM-like analysis to games. Chintagunta et al. (2009) analyzed the marketing mix in the context of video game console sales, demonstrating that econometric models can capture marketing effects in the gaming domain. While consoles are hardware and a bit different from indie games, their study confirmed that price, advertising, and network effects could be quantified. More directly, Burmester et al. (2015) studied how pre-launch publicity and advertising affected video game sales trajectories, showing that these effects could indeed be parsed and measured. These studies, though not about indie games per se, give confidence that MMM is applicable to game sales data.

Looking at the current state of practice, many mobile game companies (which often start as indie developers) have begun to adopt automated marketing analytics that resemble MMM, albeit sometimes using proprietary AI systems. They adjust advertising spend dynamically and try to attribute value to different channels. Indie PC/console game studios are starting to explore these techniques as well, especially as tools become more accessible (for example, open-source MMM packages like Robyn or Google's CausalImpact). The challenge is making it feasible – a lone indie developer likely doesn't have a data science team, so the MMM approach must be simplified or guided (which again favors Bayesian methods with informative priors that the developer can supply from general knowledge).

2.4.3. Influencer Marketing in the Indie Game Context

For many indie games, influencer marketing is not just one component of the mix – it is the central pillar of their marketing strategy. With limited funds for broad advertising, indie developers often rely on streamers, YouTubers, and gaming bloggers to get the word out (Hughes, Swaminathan, & Brooks, 2019). This reliance is bolstered by the nature of games as experience goods: potential players prefer to see the game in action (through gameplay videos or streams) to evaluate its fun factor before purchasing (Wan & Sam, 2024). The phenomenon of "Let's Play" videos – where influencers play through games while commentating – has essentially become free advertising (or sometimes paid, via sponsorship) for game developers. A well-known anecdote is that certain indie games have gone from obscurity to best-sellers overnight because a popular streamer showcased them, leading their audience to rush and buy the game. This dynamic means influencer marketing can have an outsized and rapid impact on indie game sales, more so than in many other industries.

The literature and industry case reports suggest a few strategies that indie game marketers have found effective:

- **Early access and influencer previews:** Many indie developers give out preview copies or early access to influencers ahead of launch. By building relationships with content creators who genuinely like their game, they foster organic enthusiasm that peaks at launch. This can be framed as part of the marketing mix – essentially an earned media strategy that primes the pump for launch sales.

- **Nano/Micro-influencer "army":** As discussed in 3.4, targeting a large number of small influencers can yield better ROI than a single big name. Indie games exemplify this strategy. For example, instead of paying one celebrity streamer $20k to play the game once, a developer might reach out to 100 micro-influencers with dedicated followings of the game's target genre, offering each a free key or a small sponsorship. The collective reach might rival or exceed the celebrity, and because each micro-influencer's audience is highly aligned with the game, the conversion rate is higher. Beichert et al. (2023)'s findings strongly support this approach, showing that an aggregation of nano-influencers produced a higher overall ROAS for product campaigns. In practice, indie studios have reported success with this grassroots approach – it creates word-of-mouth in multiple communities simultaneously.

- **Community building as marketing:** Indie developers often act as their own influencers to some extent, especially via platforms like Discord, Twitter, or developer live streams. Engaging directly with a community of fans can create a loyal base that not only purchases the game but advocates for it. While not "influencer marketing" in the paid sense, this overlaps with the influencer concept because the developer or their community managers become influential voices. Some analyses (e.g., industry discussions by Analytical Alley (n.d.)) suggest including community engagement metrics (like Discord active users) when modeling an indie game's marketing success, treating the community as a marketing channel in itself.

From an MMM perspective, influencer marketing's dominance in indie game promotion means any model of an indie game's marketing mix must explicitly include influencer variables to avoid misattribution. If one were to run an MMM on an indie game launch without an influencer variable, chances are the model would attribute the sales spike to whatever other variables are present (or to the baseline), which would be misleading. The earlier example of "organic lift" variables is pertinent – including measures of influencer activity (paid or unpaid) is necessary to explain the variance in sales.

There are also challenges specific to influencer marketing for indie games: an influencer-driven spike can overwhelm other signals (making it hard to disentangle in a model), and it may also saturate the potential market quickly. Indie games often have a fixed niche audience, and once that niche is reached through influencers, additional marketing may face steep diminishing returns. This is consistent with the saturation idea we discussed: influencer-driven hype can saturate the addressable market faster than traditional ads because it's often highly targeted and trusted. So an MMM might show a rapid saturation curve for the influencer channel – high impact at first, then quickly tapering – aligning with how a small community can be fully converted in a short time.

On the opportunity side, influencer marketing presents indie developers with a leverage that is disproportionate to their size. A single person streaming a game can outperform a paid ad campaign costing tens of thousands of dollars. The caveat is that it's not entirely controllable – one cannot force an influencer to like or play a game (beyond sponsorship deals, which may not be affordable or authentic). Thus, indie marketing strategies often revolve around making the game appealing to influencers (e.g., ensuring the game is enjoyable to watch, has hooks that will intrigue content creators, etc.). This notion goes a bit beyond marketing mix into product design, but it underlines how intertwined product and promotion are in this space. A well-designed indie game that caters to a streaming audience (for example, has moments that create emotional or humorous reactions on stream) effectively markets itself once it's picked up by influencers.

2.5. Research Hypotheses

This thesis investigates how different components of the marketing mix contribute to pre-launch demand for an indie video game. In line with the Marketing Mix Modeling (MMM) literature, the empirical analysis links time-varying marketing exposures to a single key outcome metric: daily Steam wishlist additions ("Adds"). The focus is on influencer-driven and earned media channels (YouTube, Twitch, Reddit, TikTok, and online press/media), which are widely discussed in the literature as relevant for digital products and experience goods.

Based on the theoretical background developed in Chapter 2, the following hypotheses are formulated:

H1 (Influencer video exposure – YouTube). Higher YouTube exposure generated by influencer videos is positively associated with daily wishlist additions, controlling for trend, seasonality, and major events.

H2 (Live streaming exposure – Twitch). Higher Twitch exposure (live streaming audience) is positively associated with daily wishlist additions.

H3 (Community discussion exposure – Reddit). Higher Reddit activity related to the game (posts and comments) is positively associated with daily wishlist additions.

H4 (Press and media coverage). Higher press/media coverage intensity is positively associated with daily wishlist additions, reflecting the credibility and reach of third-party editorial content.

H5 (Short-form video exposure – TikTok). TikTok exposure has a statistically significant relationship with daily wishlist additions. The expected direction is positive, but the effect may depend on audience and platform fit.

H6 (Influencer–product congruence as a moderator). The effectiveness of YouTube exposure is moderated by influencer–product congruence. Specifically, exposure from more congruent influencers (as defined through "indie fit" and/or "genre fit") is expected to have a stronger positive association with daily wishlist additions than exposure from less congruent influencers.

H7 (High-impact product events). Major product-related events (Demo release and Playtest period) generate a positive structural lift in daily wishlist additions beyond what is explained by continuous marketing exposures.

Empirically, hypotheses H1–H5 are tested through the sign and statistical significance of channel coefficients in the aggregated MMM specification. H6 is tested by comparing coefficients across congruence-defined exposure groups and by applying Wald tests to assess whether coefficient differences are statistically significant. H7 is tested through the sign and significance of event dummy coefficients in the time-series regression framework.

3 | Methodology

3.1. Research Design and Objective

The core outcome metric is defined as daily Steam wishlist additions (“Adds”), tracked over a 160-day period. An “Add” occurs when a user adds the game to their Steam wishlist, indicating purchase interest. This metric was chosen because wishlists are a crucial precursor to sales for upcoming games, reflecting accumulated consumer interest prior to release. By modeling daily Adds, we capture the incremental effects of marketing activities on building player interest.

The research adopts a time-series regression design in which daily Adds (the dependent variable) are regressed on time-varying marketing exposures across multiple channels. The objective is to isolate the contribution of each marketing channel to driving wishlist additions, while controlling for confounding factors and temporal effects. MMM leverages aggregated time-series data to infer effectiveness by exploiting variation in daily marketing levels. The identification strategy relies on natural fluctuations in exposures over time and the inclusion of control variables to account for trends and seasonality. In essence, we assume that if an increase in a channel’s activity (e.g. a burst of YouTube views) is consistently followed by a rise in wishlists (with other factors held constant), the model can attribute a portion of that lift to the channel.

3.2. Data Sources and Variable Construction

Data on daily marketing exposures were collected from five key channels: YouTube, Twitch, Reddit, TikTok, and Press/Media. Each channel’s raw exposure data was gathered from publicly available statistics (social media platforms, content analytics, and press archives) and then processed into time-series variables. All marketing variables are aligned to the same daily timeline (160 consecutive days). We constructed each independent variable as follows:

- **YouTube (Influencer Videos):** This channel consisted of YouTube videos by gaming influencers featuring the indie game. Exposure was measured as daily video view counts. Since YouTube views distribution isn't available for public, we calculated views distribution based on comments time stamps exported via YouTube API. Because YouTube content can generate views for days or weeks after release, we applied an **adstock transformation** to model carryover: specifically, a geometric adstock with a retention factor λ_{YT}. This means an initial spike in views from a video has a decaying impact on subsequent days' Adds. Prior to adstocking, we took a log-transform: $X_{\text{YouTube},t} = \log(1 + \text{adstocked views}_t)$. The $\log(1+x)$ dampens extreme spikes and reflects diminishing returns (the first few thousand views likely generate more wishlists per view than later views). In our data, YouTube exposures were sporadic spikes corresponding to influencer uploads, so adstock ensures those spikes influence adjacent days rather than a one-day binary effect.

- **Twitch (Live Streaming):** Twitch exposure was tracked via the peak concurrent viewers watching any Twitch streams of the game each day – that is the only data set available. This metric captures the maximum live audience size on that day, which serves as a proxy for the reach of Twitch content. (The game's Twitch presence was characterized by a few streaming events rather than continuous coverage, hence using peak viewers rather than hours watched or average viewers). We log-transformed the daily peak viewers ($\log(1 + \text{peak viewers})$). After testing, we treated Twitch exposure as mostly instantaneous (little carryover), since live streams drive immediate interest that tapers off once the stream ends. Indeed, preliminary model tuning indicated a near-zero optimal adstock retention for Twitch, so in the final model we effectively use $\lambda_{\text{Twitch}} \approx 0$ (no multi-day decay) – each day's Twitch impact is isolated to that day. On days with no Twitch streams for the game, the exposure is zero (which becomes 0 after log(1+0)).

- **Reddit (Online Discussions):** Reddit exposure was measured by tracking posts about the game we published. We compiled daily counts of Reddit posts and comments referencing the game, focusing on gaming communities (e.g., r/IndieGaming, r/Games, and other relevant subreddits). No geometric adstock was applied – it was possible to build approximate views distribution based on comments time stamps exported from Reddit API.

- **TikTok (Short-Form Video):** TikTok exposure was measured by views on TikTok videos about the game. The game's developers and a few influencers posted short videos (e.g., gameplay clips). We summed daily TikTok views and applied log(1+x). We assumed TikTok content, like YouTube, can generate views over several days as it gets picked up by the algorithm, so we initially allowed a relatively

long adstock tail ($\lambda \approx 0.9$, half-life ~6–7 days) for TikTok views. This reflects that TikTok videos might continue to be recommended/shown for about a week.

- **Press/Media (Articles and Features):** This variable captures coverage of the game in online media outlets (gaming news sites, blogs, etc.) and YouTube news segments (distinct from influencer gameplay videos). We recorded each day that a press article or major blog post about the game was published. Exposure was quantified as dummy variable as it is not possible to now exact reach count for media outlets. Because articles can continue to drive traffic as they are read and shared, we gave Media exposures a long adstock ($\lambda \approx 0.9$, half-life ~6 days, similar to TikTok). Essentially, a press mention was treated as having a week-long residual effect on accumulating wishlists (someone might see an article days later). We then took $\log(1 + \text{adstocked article count})$. This approach weights a burst of press coverage as having a lasting presence.

Control variables and data processing: All marketing variables were aligned by date, with any missing exposure data imputed as 0 (no activity). Prior to modeling, each channel's time series was inspected for anomalies and seasonality. We added **day-of-week indicators** to capture systematic differences in user behavior (e.g., weekend vs weekday patterns in Steam usage) and a continuous **trend** term to capture any baseline growth in wishlist activity over time (e.g., increasing awareness as release approaches). Two major event dummies (described in 3.3) were also added. These controls ensure that the marketing coefficients are not biased by regular cyclical patterns or unrelated one-off events.

In the end, the dataset is a panel of 160 daily observations with around 5–7 key regressors (in the aggregated model) plus controls. This data construction enables the regression to exploit temporal variation in exposures, both within and across channels, to estimate their impact on daily Adds.

3.3. Model Specification

We estimated a **log-linear regression model** with Newey–West heteroskedasticity-autocorrelation consistent (HAC) standard errors. The general specification for the baseline (aggregated) MMM is:

$$\log\left(1+\text{Adds}_t\right)=\beta_0+\sum_{c\in\{\text{YT,Twitch,Reddit,TikTok,Media}\}}\beta_c\,\log\left(1+X^{\text{adstock}}_{c,t}\right)+\beta_{\text{trend}}\,(t)+\sum_{d=2}^{7}\gamma_d D_{d,t}+\delta_1\text{Demo}_t+\delta_2$$

where:

- $\log\left(1+\text{Adds}_t\right)$ is the dependent variable (log of daily wishlists adds).

- X is the adstock-transformed exposure for channel c on day t (as constructed in 3.2), and β_c is its coefficient (elasticity of Adds w.r.t that channel).

- t (in $\beta_{\text{trend}}(t)$) is a linear time trend (1,2,3,...,160).

- $D_{d,t}$ are day-of-week dummy variables (for Tuesday through Sunday, with Monday as baseline) to control for weekly seasonality in player activity.

- Demo_t *and* Playtest_t are binary indicators for two high-impact events: the release of a free public **Demo** version of the game, and a limited **Playtest** period (closed beta) that occurred on specific dates.

These capture sudden large shifts in Adds due to these events (beyond what continuous marketing variables explain). We code Demo and Playtest as 1 on days corresponding to the events (and possibly immediately after, if the event effect is expected to persist a day). Including these dummies helps isolate organic boosts not attributable to the usual marketing channels.

- ε_t is the error term. We detected some positive autocorrelation in residuals (Durbin–Watson $\approx$ 1.07 in the initial model), likely due to time-series effects not fully captured by our controls. Thus, we employ **Newey–West standard errors** (lag=7 days) to obtain robust p-values that account for up to a week of autocorrelation. This means coefficient significance tests are adjusted for the fact that daily adds might have week-to-week correlation (e.g., trending up or down across consecutive days).

The model is estimated on the 160-day sample, but we also evaluate it on a **holdout set** (described below). Goodness-of-fit is assessed with R^2 (on log-scale predictions) and standard error metrics (RMSE, MAE on the original Adds scale), as well as information criteria (AIC, BIC) to penalize model complexity.

We estimated three main variants of the MMM to address the research questions:

1. **Aggregated Model (Platform-level):** This is the baseline as specified above, where each channel is one variable (e.g., all YouTube exposures aggregated). This model is

parsimonious (fewer parameters) and provides an overview of which platform contributes most to wishlists. However, it treats all influencers or content within a platform as homogeneous and may mask differences (e.g., a large vs small YouTuber might have different effectiveness). It also initially treated Reddit as a single variable.

2. **Decomposed Model (Influencer-level, v1):** To gain granular insight, we disaggregated the YouTube and Reddit variables into multiple variables. For YouTube, we included separate regressors for individual influencers' video views. In practice, only the top influencers (those who created significant content for the game) were entered to avoid overfitting – specifically, 8–10 YouTube variables representing distinct creators (or specific viral videos) were used. Similarly, Reddit exposure was decomposed by major posts or communities – for example, a separate variable for an AMA thread vs. a news post vs. monthly "Indie Sunday" threads on r/Games. Each such variable had its own adstock (if applicable).

3. **Decomposed v2 (Revised):** In the final revised decomposed model, we introduced improvements based on learnings from v1. We separated Reddit exposures by individual high-impact threads rather than lumping all Reddit activity, since different posts had distinct timing and lifecycles. We also revisited adstock "tails": for v2, we allowed longer decay for certain influencer videos that continued gaining views, and we constrained Twitch's adstock to zero (instant effect) given that a long carryover for Twitch in v1 seemed conceptually wrong and contributed to overfitting. Decomposed v2 thus represents our best specified model for channel-level effects with maximal interpretability. It has many more parameters than the aggregated model, so we expect a higher in-sample R^2 but potentially reduced stability.

All models were evaluated on both in-sample fit (the full 160 days) and a holdout set. We reserved a portion of data (e.g., the final 20 days) as a holdout to test out-of-sample predictive performance. We report the holdout R^2(which indicates how well the model predicted unseen data) and holdout RMSE/MAE. This guards against overfitting: a model that memorizes noise will have high in-sample R^2 but poor holdout R^2. We also compare AIC and BIC for model selection. AIC/BIC penalize model complexity: lower values indicate a better balance of fit and parsimony. In terms of estimation technique, all models were estimated using ordinary least squares (OLS).

To summarize, our methodology entails building a robust time-series regression model of daily wishlist adds, with careful feature engineering (log, adstock, dummies) and multiple model variants to balance detail vs. reliability. The next sections detail the novel aspect of this study: incorporating influencer–product congruence into the model specification.

3.4. Congruence Operationalization

A key extension of this research is to examine whether the fit between an influencer and the product (game) affects marketing effectiveness. We operationalized **influencer–product congruence** ex ante (before modeling) by classifying each influencer who created content about the game along two binary dimensions:

- **“Indie Fit”** – Does the influencer typically focus on indie games (versus primarily AAA/mainstream titles)? This indicates channel–product fit in terms of production scope and audience expectation for indie content.

- **“Genre Fit”** – Does the influencer regularly cover games of the same genre as ours? This captures content–product fit in terms of thematic or gameplay genre alignment.

Each influencer was assigned an **indie_fit = 1 or 0** and **genre_fit = 1 or 0**. For example, an influencer known for spotlighting indie titles would get indie_fit = 1; if that influencer also frequently plays RPGs (and our game is an RPG), they get genre_fit = 1 (thus falling in the both-fit category). These binary flags were determined through a **codebook of decision rules** using the influencers' historical content profiles:

- Indie Fit: We reviewed the channel content of each YouTuber in the months leading up to the campaign. Influencers were labeled **Indie-fit (1)** if a substantial portion of their content focuses on indie or niche games. A concrete rule was: if more than 50% of their last 20 gameplay videos were indie games (or if their channel branding emphasizes indie games), we marked them as indie-focused.

- Genre Fit: We first identified our game's genre attributes – suppose the game is an **open-world fantasy RPG** (role-playing game). We then assessed whether the influencer commonly plays similar genres (open-world RPGs or related subgenres). An influencer was labeled **Genre-fit (1)** if their content history showed a clear pattern of covering RPGs or comparable genres (for example, channels known for RPG playthroughs, or who have covered many titles in the Elder Scrolls/Fallout series would be genre_fit = 1). Those who seldom or never feature RPGs (maybe they focus on strategy or horror instead) were marked genre_fit = 0. This classification was based on the past year of videos and channel descriptions. We also cross-checked tags or game lists for each influencer to ensure consistent coding.

3.5. Congruence Model Construction

To examine the impact of influencer–product congruence on marketing effectiveness, we built modified MMM models where YouTube exposures are segmented by congruence groups. Rather than a single aggregated YouTube variable, we created separate variables for congruence-defined subgroups of influencers. We implemented two main model variants (A and B), and an exploratory variant (C):

- **Model A – Indie-fit vs Non-indie:** In this model, we split YouTube exposure into two regressors: one for Indie-fit influencers and one for Non–Indie-fit influencers.
- **Model B – Genre-fit vs Non-genre:** This parallel model splits YouTube exposures by genre alignment.
- **Model C – Quadrant (Indie × Genre) Segmentation:** As an exploratory extension, we combined the two dimensions to see if both forms of fit together have an interaction effect.

In all congruence models, Twitch was not decomposed by congruence. The reasoning is twofold: First, Twitch data was available only as an aggregated peak viewer count per day, not broken down by which streamer contributed how many viewers. We lacked detailed streamer-by-streamer viewership data that would be needed to classify Twitch streamers into fit vs non-fit groups. Second, the Twitch exposure in this campaign was dominated by one-off streams by a couple of variety streamers; there wasn't a rich set of Twitch influencers to segment. As such, we left Twitch as a single variable (peak concurrent viewers) in the congruence models, assuming its effect is homogeneous.

Finally, we maintained the Demo and Playtest event dummies in all these models to account for those big shocks. We anticipated that in the congruence models, some variance that the event dummy captured in the aggregated model might instead be explained by one of the exposure subgroups (e.g., perhaps the demo release coincided with many genre-fit YouTubers posting videos, etc.). We decided to keep the event controls to ensure a fair comparison of channel coefficients with and without congruence segmentation.

To evaluate the congruence models (A, B, C), we used the same metrics: in-sample fit (R^2, AIC/BIC) and holdout performance. We also conducted **Wald tests** to directly compare the coefficients of fit vs non-fit groups (e.g., $H_0 : \beta_{\text{YT,indie}} = \beta_{\text{YT,non-indie}}$) to see if differences were statistically significant. These models help answer whether incorporating influencer–product fit yields better explanatory power or reveals meaningful differences in channel effectiveness.

4 | Results

4.1. Model Overview and Comparison

We estimated and compared the five main models (aggregated, decomposed v2, and congruence variants) to assess model fit, stability, and interpretability. **Table 4.1** summarizes key performance metrics:

Characteristic	**Aggregated (v2)**	**Decomposed (v2)**	**Genre fit**	**Indie fit**	**Quadrant**
YouTube decomposition	total	by video	by fit group (2)	by fit group (2)	by quadrants (4)
Reddit decomposition	total	by post	total	total	total
Number of parameters (k)	15	32	24	24	25
λ YouTube	0.6	0.6	0.0	0.0	0.0
λ Reddit	0.3	0.3	0.6	0.6	0.6
λ Twitch	0.0	0.9	0.0	0.0	0.0
λ Press/Media	0.9	0.6	0.3	0.3	0.3
R^2 (Adds)	0.812	0.915	0.697	0.702	0.678
R^2 (log)	0.866	0.915	0.827	0.827	0.828
RMSE (Adds)	90.5	60.7	114.7	113.9	118.3
MAE (Adds)	44.2	29.7	51.7	51.6	53.3
MAPE	31.7%	23.6%	36.2%	36.1%	35.9%
AIC (log)	170.8	131.5	229.1	228.6	229.9
BIC (log)	216.9	229.9	302.9	302.4	306.8
Durbin–Watson (residuals, log)	1.07	1.22	1.27	1.26	1.24

- **Aggregated MMM (platform-level):** This simpler model achieved an **in-sample**

R^2 of approximately 0.86 (Adj. $R^2 \approx 0.85$), indicating it explained ~85% of the variance in log daily Adds. The in-sample Root Mean Squared Error was about 90.5 adds, and Mean Absolute Error ~44 adds (on days with an average of ~50–60 adds, this is a reasonable error). The model's AIC (≈171) and BIC (≈217) were moderate. With only 5 marketing variables + 2 events + controls, the aggregated model is parsimonious and had no overfitting signs in-sample. We did a simple holdout test (reserving the last few weeks): although exact holdout R^2 for this model was not directly computed in early runs, the aggregated model showed robust generalization — qualitatively, its predictions did not wildly overshoot in the holdout period, suggesting it captured the main patterns without chasing noise. Its interpretability is high: coefficients directly tell us the elasticity of Adds with respect to each channel overall. However, the limitation is that it treats, say, all YouTube videos as one combined effect, which could obscure differences between individual influencers or content types.

- **Decomposed MMM (influencer-level, revised):** The final refined decomposed model (with disaggregated YouTube by influencer and Reddit by post) delivered a very high **in-sample R^2 of 0.915** ($Adj.R^2 \approx 0.894$). This means ~91.5% of the variance in log Adds was explained – an excellent fit. The model was able to almost "connect the dots" of every major spike in wishlists by attributing them to specific marketing inputs. Information criteria, however, reflected its complexity: BIC was ~230 (higher is worse, compared to 217 in aggregated), and AIC ~131 (lower than aggregated's 171, indicating much better goodness-of-fit relative to penalty). The decomposed model had many parameters (roughly 10 influencer variables + 5 Reddit variables + others), which risk overfitting. Indeed, when we evaluated holdout performance, the decomposed model failed to generalize: holdout R^2 was negative (approximately -0.47). A negative holdout R^2 means the model did worse than a naive mean prediction on new data – essentially, it overfit the noise in the training set. This overfitting is also indicated by Durbin–Watson ~1.22 (still some autocorrelation left) and by relatively unstable coefficient estimates for some collinear variables (large standard errors). Interpretability, on the other hand, was rich: the decomposed model outputs allow us to see which particular YouTuber or Reddit thread had significant impact (e.g., a variable for "Influencer X's video" with coefficient Y). We found, for instance, that a Reddit post referencing Morrowind contributed strongly (significant positive coefficient), whereas a post on r/ElderScrolls had a negative coefficient (likely a suppression or negative discussion – the post was deleted later by moderator of subreddit) in the context of other variables – such granular insights are only possible with decomposition. Yet, many of these granular effects come with wide confidence intervals and multicollinearity concerns, so individual interpretations must be made cautiously. In summary, the decomposed model maximized fit at the cost of stability: it explains the historical data extremely well, but its predictions for future data are unreliable, implying some overfitting to that particular 160-day sample.

- **Congruence-augmented models:** We estimated three versions (indie-fit, genre-fit, quadrants) – their performance was very similar to each other, so we describe them collectively here. These models had an **in-sample $\mathbf{R^2 \approx 0.827 - 0.828}$** (Adj. $R^2 \approx 0.798$), notably lower than the aggregated model's 0.86. This drop in fit is expected because we reduced the flexibility of the YouTube representation (from one variable to two, but with simpler dynamics – no long adstock) and effectively removed some degrees of freedom (the congruence models did not include individual influencer variables, only grouped ones). In absolute terms, they explained ~82.7% of variance, which is still respectable but indicates a modest underfit relative to the aggregated model on training data. Their AIC (~229) and BIC (~302) were higher (worse) than both aggregated and decomposed models, reflecting that these models neither fit as well as decomposed nor are as simple as aggregated. However, holdout performance told a different story: the congruence models achieved holdout $R^2 \approx 0.37 - 0.38$, meaning they explained ~37% of the variance in unseen data – a huge improvement over the decomposed model's -47%. In fact, the holdout R^2 of ~0.38 suggests that while these models underfit a bit in-sample, they generalize far better. This implies the congruence grouping may be capturing the essential structure of how YouTube drives adds (with fewer parameters) without chasing random fluctuations. Thus, in terms of **stability**, the congruence models strike a middle ground: they forgo the over-detailed influencer-by-influencer fitting in favor of broader categories, which avoids overfitting and yields better predictive accuracy than the fully decomposed approach. They are slightly more complex than the plain aggregated model, but the added complexity is theory-driven (based on fit segmentation) rather than data-mining-driven.

Interpretability and insights: The aggregated model is straightforward to interpret at the channel level ("YouTube elasticity is X, Twitch is Y, etc."), making it useful for high-level media mix decisions. The decomposed model provides micro-level insight (which exact influencers or posts mattered), valuable for forensic analysis and future influencer selection, but it proved too unstable for reliable planning. The congruence models, on the other hand, offer a theoretically informed interpretation: we can interpret coefficients for "fit" vs "non-fit" groups, which speaks to influencer marketing theory (does congruence make a difference?) and provides actionable guidance (e.g., whether to prioritize indie-specialist influencers). The congruence approach simplifies the influencer heterogeneity into a couple of variables, thus remaining more robust. While these models sacrificed some raw fit, they still explained the majority of variance and yielded easier-to-generalize findings.

Ultimately, for practical use, one might favor a model that balances interpretability and predictive power – the congruence segmentation seems to achieve that by incorporating domain knowledge (influencer type) into the regression. Next, we delve into the detailed results for each channel and factor, referencing primarily the aggregated model for channel effects, and then assessing the congruence effects from the specialized models.

4.2. Effectiveness by Channel

Using the aggregated MMM as the primary reference (supplemented by consistent findings in the decomposed model), we assess each marketing channel's effectiveness in driving Steam wishlist additions. Table 4.2 presents the estimated coefficients (elasticities) for each channel with Newey–West adjusted significance levels:

Characteristic	**YouTube (Influencer videos)**	**Twitch (Live streaming)**	**Reddit (Community discussions)**	**TikTok (Short videos)**	**Press / Media**
Exposure proxy (daily)	Total YouTube views (all influencers, aggregated)	Peak concurrent viewers	Mentions/posts/comments count	TikTok views	Count of press/media pieces (coverage intensity)
Elasticity β (Adds)	**+0.09**	**+0.10**	**+0.10**	**-0.09**	**+0.12**
HAC SE	0.019	0.019	0.019	0.031	0.034
t-stat	4.81	5.14	~5.14	-2.87	3.53
p-value	<0.001	<0.001	<0.001	0.0047	<0.001

Characteristic	YouTube (Influencer videos)	Twitch (Live streaming)	Reddit (Community discussions)	TikTok (Short videos)	Press / Media
Modeled attribution (share of incremental adds)	~41%	~10%	~22%	—	~41%

These estimates directly test H1–H5. Overall, H1–H4 are supported (positive and statistically significant coefficients for YouTube, Twitch, Reddit, and Press/Media), whereas H5 is rejected because TikTok shows a statistically significant effect with the opposite (negative) sign.

- **YouTube (Influencer Videos):** We found a **positive and significant effect** of YouTube exposure on daily wishlists. The elasticity of Adds with respect to YouTube views was approximately β_{YouTube}≈**0.09** (*HAC SE* ≈ 0.019, t ≈ 4.81, p < 0.001). This implies that a 1% increase in YouTube video views (across all influencers) is associated with roughly a 0.09% increase in daily Adds, holding other factors constant. In practical terms, if an influencer video doubled its views from, say, 50k to 100k (a 100% increase), we'd predict about a ~6–7% uplift in wishlists that day. This underscores YouTube as one of the most influential channels in generating interest. The positive coefficient aligns with expectations: YouTube gameplay videos allow potential players to visualize the game, stimulating them to wishlist. The decomposed model further showed that almost all major YouTubers had positive contributions (no influencer had a significantly negative impact on wishlists), reinforcing that YouTube content in general was effective. The effect size (0.09 elasticity) is moderate, suggesting diminishing returns – enormous view counts are needed to double the wishlists, consistent with a funnel where only a fraction of viewers take action. Still, among channels, YouTube's contribution was substantial (in the aggregated model's attribution, YouTube accounted for ~41% of the explained incremental adds). Therefore, H1 is supported.
- **Twitch (Live Streaming):** Twitch also exhibited a **significant positive impact**, with an elasticity around β_{Twitch}≈**0.10** (SE ~0.019, t ≈ 5.14, p < 0.001). This coefficient is of similar magnitude to YouTube's. However, it's important to interpret

it in context: Twitch exposure was measured by peak concurrent viewers, which is a different metric than cumulative views. A 1% increase in peak viewers (for instance, 2000 to 2020 viewers) yields ~0.10% more wishlists. Given Twitch peaks in our data were on the order of a few thousands at most, the overall impact of Twitch was smaller in absolute terms (contributing ~10% of total modeled adds), because there were fewer major Twitch events compared to the sustained presence of YouTube videos. Notably, Twitch's effect was immediate – our final model did not carry over any Twitch influence to subsequent days (consistent with the transient nature of live streams). The significance of the coefficient ($p < 0.001$) suggests that even though Twitch events were infrequent, when they did occur (e.g., a big streamer), the model detected a clear uptick in wishlists that day attributable to those streams. One interpretation is that live streams create urgency or strong interest among a core audience, prompting an immediate reaction (wishlist add) during or right after the stream. Therefore, H2 is supported.

- **Reddit (Community Discussions):** Reddit activity had a **positive, significant effect** on wishlists with an elasticity around $\beta_{\text{Reddit}} \approx \mathbf{0.10}$ (SE ~0.019, $t \approx 5.14$, $p < 0.001$, virtually the same t-stat as Twitch in the aggregated model). This indicates that a surge in Reddit mentions (posts/comments) by 1% correlates with ~0.10% more adds. Given how we measured Reddit (count of mentions), a single popular thread (with many comments) in one day can drastically increase that day's "mentions" count. The model suggests such spikes indeed boosted wishlists. For example, one of the largest Reddit events was a humorous post comparing the game to Elder Scrolls: Morrowind that went somewhat viral; the decomposed model gave that particular post a strongly significant coefficient, confirming its impact. In the aggregated view, Reddit contributed roughly 22% of modeled adds increment, which is meaningful. Reddit's half-life was short (most effect same day), and accordingly, the model coefficient captures largely immediate impact. Intuitively, when the game was trending on Reddit, many users likely clicked through to Steam and wishlisted in that moment. All considered, Reddit proved to be an important organic channel – every burst of community discussion visibly translated into more wishlists, underlining the value of social buzz and peer recommendations. Therefore, H3 is supported.

- **TikTok (Short Videos):** TikTok's coefficient came out **negative and statistically significant** in the aggregated model (approximately $\beta_{\text{TikTok}} \approx \mathbf{-0.09}$, SE ~0.031, $t \approx -2.87$, $p = 0.0047$). A negative elasticity implies that higher TikTok views were associated with lower wishlist additions, after controlling for other factors. This result seems counter-intuitive at face value – one wouldn't expect marketing to have a truly negative causal effect. There are a few possible explanations. TikTok content might have been released during periods when other marketing was quiet or when interest was naturally waning, so the model attributes a decline trend to TikTok. For instance, if TikTok posts were made as a "last resort" during slow days, the slow day's low Adds might correlate with TikTok presence. Regardless of cause, the negative coefficient suggests that on the margin, TikTok marketing did not help wishlist numbers and might have coincided with slightly lower numbers. We interpret this cautiously: it likely does not mean TikTok content actively discouraged wishlisting (more likely it had minimal direct effect, and the negative sign is an artifact of interactions with other channels or timing). The practical takeaway is that TikTok was not a productive channel in this case, and resources spent there did not yield visible results. The significance ($p < 0.01$) indicates this finding is statistically robust in the model, but again, causally one should be careful – it might be reflecting strategy (e.g., devs put content on TikTok when other hype was low). In subsequent models (with decomposition and congruence), TikTok's coefficient sometimes became statistically insignificant (as some variance was reallocated to trend or other factors), but it never showed a positive impact. This consistently points to TikTok's limited or negative efficiency for this particular game's campaign. Therefore, H5 is rejected in this study: TikTok exposure is statistically significant, but the estimated association is negative rather than positive.

- **Press/Media:** This channel had the **largest positive coefficient** among all, about β_{Media}≈**0.12** (SE ~0.034, $t \approx 3.53$, $p < 0.001$) in the aggregated model. A 0.12 elasticity means a 1% increase in media yields ~0.12% more wishlists. Press articles are relatively infrequent but when they occurred, they often coincided with major beats (e.g., the demo release had several articles on gaming websites). The model attributed a significant chunk of wishlist additions to press – about 41% of incremental adds were credited to media coverage, the single largest share. Part of this is because press often works in tandem with events: for instance, on the day of the demo launch, multiple press outlets wrote about the game, leading to a big spike in wishlists. Press articles likely reach broader audiences (including those not actively searching on YouTube/Reddit), and they lend credibility. For an indie game, a feature on a site like PC Gamer or RockPaperShotgun can drive thousands of people to check out the Steam page. Our results confirm this: being covered in gaming press correlates with sharp increases in wishlists. The long adstock for Media means an article's influence was felt for several days; indeed, we saw that after a major article, wishlist additions remained above baseline for about a week (consistent with the half-life ~6 days assumption). Thus, traditional media and blog coverage had a highly effective and lasting impact on accumulating wishlists – arguably more so than an equivalent exposure on social media, perhaps due to the broader reach or higher trust in editorial content. Therefore, H4 is supported.

All coefficients discussed are based on HAC standard errors, so we are confident these significance levels account for auto-correlation (e.g., the t-stats remain high even after adjusting for any lingering time-series effects). The effect sizes, while seemingly small in elasticity terms, must be viewed in light of large exposure swings – e.g., a well-timed Reddit post or press article can double or triple relevant exposure metrics, which in turn (via elasticity ~0.1) can yield 10–20% jumps in daily wishlists, a meaningful lift.

4.3. High-Impact Events

Beyond continuous marketing variables, our model included binary indicators for two high-impact events that were hypothesized to greatly affect wishlists: Demo Release (free public demo availability) and Playtest Event (closed beta test invitation).

Characteristic	Demo Release	Playtest Event
Event type	Free public demo becomes available	Closed / invite-only beta playtest period
Model variable	Binary dummy (1 on demo launch day)	Binary dummy (1 during playtest launch)
Estimated coefficient (δ)	$\approx$ **2.01**	$\approx$ **0.29**
HAC SE	≈ 0.26	≈ 0.11
t-stat	≈ 7.74	≈ 2.50
p-value	$<$ **0.001**	**0.014**
Log-linear interpretation	$+2.01$ in log(Adds) on event day	$+0.29$ in log(Adds) during playtest days
Multiplicative lift (exp(δ))	**e^2.01** $\approx$ **7.5**$\times$ baseline Adds	**e^0.29** $\approx$ **1.33**$\times$ baseline Adds
Percent lift	~**+650%** vs baseline	~**+33%** vs baseline

Demo Release: The demo launch had a dramatic effect on wishlist additions. In the aggregated model, the Demo dummy coefficient was estimated around $\delta_{\text{Demo}} \approx 2.01$ (HAC

SE ≈ 0.26, $t \approx 7.74$, $p < 0.001$). Indeed, looking at the raw data, the day the Steam demo went live saw an enormous spike in wishlists (from typical values in the dozens up to nearly 200 Adds on that day, an all-time high for the period). Our controls and other channels explain part of that jump (press coverage, YouTube videos, Reddit buzz all happened then), but the Demo dummy still captures a large unexplained increase. This likely represents organic Steam platform effects: when a demo is released, Steam may feature the game in "New & Trending" or the game gains viral traction as players actually try it. Mechanistically, one can think that prior marketing primed people, but the demo provided the trigger for action. It's worth noting in the congruence models, where press and influencer variables soak up more variance, the demo dummy became less significant – suggesting much of the demo's impact came through those channels: influencers making videos of the demo, press reviews of the demo, etc. Nonetheless, even after accounting for those, having a hands-on trial available gave an extra boost.

Playtest Event: The closed playtest (a period where selected players could play a beta) also showed a positive effect, though smaller than the demo. In the aggregated model, the Playtest dummy coefficient was about $\delta_{\text{Playtest}} \approx 0.29$ (SE ≈ 0.11, $t \approx 2.50$, $p = 0.014$). This corresponds to roughly a 33% increase in daily adds during the playtest (since $e^{0.285} \approx 1.33$). The playtest was a more limited event (fewer users had access, and it wasn't as publicly visible as a free demo). Still, the model finds it significantly raised wishlists above baseline. The mechanism here likely involves word-of-mouth and community engagement: the select players who got in may have streamed or discussed their experience (drawing others to wishlist in hopes of future access), and the exclusivity itself created a mini hype. It might have also coincided with an announcement that the playtest was happening, which acts as marketing in itself ("sign up now" messaging). The moderate effect size (30–50% bump for a short period) is reasonable – it's smaller than the demo because fewer people directly experienced the game, but it's not negligible. The playtest's effect appears significant at the 95% level in aggregated model, though in congruence models it turned insignificant likely because its variance overlapped with other predictors like day-of-week or minor media beats.

Mechanisms and context: Both Demo and Playtest can be seen as product-driven stimuli rather than pure marketing spends. The Demo gave a substantial algorithmic boost on Steam – when many people download or play a demo, the Steam store may surface the game to more users (via friend activity feeds, "Popular Upcoming" lists, etc.), creating a virtuous cycle of visibility. Additionally, the demo generated new content: many YouTubers and streamers featured the demo (free content to showcase), and press wrote first-impression articles – amplifying marketing indirectly. The model had to use a dummy to soak up what couldn't be explained by our existing media variables, but in reality the demo's effect was partly mediated by those channels (which is why those channels also spiked). In short, the demo served as a catalyst that amplified all marketing efforts and also directly converted store page visitors at a higher rate (someone who played the demo and liked it is very likely to wishlist).

The Playtest had a different dynamic: it was closed, so one couldn't just try the game unless invited. This exclusivity might have spurred people to wishlist in hopes of getting into a future test or to follow the game's progress. It also likely engaged core community members (like those on Discord or following closely), who then might talk about it on Reddit or other forums. The fact we see a ~30% bump suggests the playtest still meaningfully moved the needle, validating the strategy of having an early access period for fans.

In practical terms, these event effects highlight that product-centric events can overshadow regular marketing. The demo in particular had a transformational impact on the wishlist trajectory (a single day accounted for a huge portion of total wishlists in the period). For an indie developer, this implies that planning a playable demo or time-limited event can be one of the most effective tactics to drive interest, especially when combined with press and influencer coverage.

Finally, we note that we controlled for day-of-week effects as well. The model found a pattern consistent with Steam user behavior: weekends saw higher organic adds than weekdays. In the aggregated model, the coefficients for Saturday and Sunday (if Monday is baseline) were positive (e.g., ~0.45 for Saturday, ~0.29 for Sunday, both $p < 0.05$), indicating ~57% and ~33% higher adds on weekends vs Monday, holding marketing constant. This likely reflects more leisure time for users to browse and add games. We mention this to contextualize that our event effects are above and beyond such temporal patterns.

In summary, high-impact events had substantial effects: the Demo release in particular was a game-changer, boosting wishlists roughly 7-fold on its launch day (and presumably continuing to have residual effects beyond that day, as seen by sustained higher adds in the week after). The Playtest provided a significant but smaller bump (~30%). These findings emphasize the importance of major beats in the marketing campaign – they create spikes that far exceed the day-to-day contributions of incremental marketing spend. Any model of marketing effectiveness should thus account for such events, as we did, to avoid attributing their large effects incorrectly to ongoing media variables. Therefore, H7 is supported.

4.4. Congruence Study

Using the specialized models described in Section 3.5, we evaluated whether influencers who were a closer "fit" for the game yielded stronger effects on wishlists than those who were less congruent. The results are presented in three parts corresponding to our three congruence model variants:

A. Indie-Fit vs Non-Indie Influencers: In Model A, YouTube exposures were split between indie-focused influencers and non-indie-focused influencers. Both groups showed significant positive coefficients, but we did not find a statistically significant difference between them. Specifically, the elasticity for indie-focused YouTubers was about 0.063 ($HAC\ SE \approx 0.011$) and for non-indie-focused YouTubers about 0.052 (SE $\approx$ 0.019). Both coefficients were highly significant on their own ($p < 0.001$), indicating that videos from either type of influencer drove wishlists. A Wald test comparing the two yielded $p = 0.43$, meaning the ~0.011 difference in coefficients (indie 0.0629 vs non-indie 0.0517) was not statistically different from zero. In practical terms, this suggests that an additional 1% of views from an indie specialist yields ~0.063% more adds, whereas 1% more views from a mainstream influencer yields ~0.052% more adds – a slightly lower point estimate for non-indie, but within error bounds of the indie group. We interpret this as no strong evidence of an "indie bonus" in our data. Both categories of influencer were effective in converting their audience's views into wishlists. It appears that mainstream gaming influencers who covered the game did nearly as well at generating interest as the dedicated indie channels. This finding is noteworthy: one might expect indie-focused creators to have more enthusiastic audiences for an indie title (thus higher conversion), but it didn't materialize as a large difference. One possible reason is that the game's quality or appeal was high enough that even viewers on general channels got interested. Another reason could be overlapping audiences – many viewers of mainstream channels might also play indies if recommended. It's also possible that our sample of "non-indie" influencers still had some affinity (they weren't completely random – e.g., some might be variety gamers who do play indies occasionally, even if not their focus). In sum, while the point estimates hint that indie specialists were marginally more effective, the difference is too small relative to uncertainty to draw a firm conclusion. Both indie and non-indie influencers substantially drove wishlists, and focusing exclusively on indie specialists did not vastly outperform outreach to general gaming influencers in this case.

B. Genre-Fit vs Non-Genre Influencers: Model B separated YouTube exposures by genre alignment (RPG-focused vs not). Here again, both groups had positive significant impacts, with no significant difference between them. The genre-fit influencers had an elasticity around 0.056 (SE ≈ 0.013), and non-genre influencers about 0.060 (SE ≈ 0.018). Somewhat unexpectedly, the non-genre group's coefficient was slightly higher (0.06 vs 0.056), though both are within each other's confidence intervals. The Wald test for difference gave p ≈ 0.83, essentially indicating no difference at all. This means an influencer whose content is usually in the same genre (e.g., RPG games) was not statistically more effective at generating wishlists than one who typically covers other genres. This result was surprising given theories of thematic congruence – one might assume an RPG YouTuber's audience would be more receptive to an indie RPG. However, our data suggests that any gaming influencer's endorsement carried weight, regardless of strict genre focus. A possible explanation is that many gamers have diverse tastes: an audience might follow a creator for personality or general gaming interest, not solely for one genre. As long as the game looked appealing, viewers wishlisted it even if it wasn't the channel's usual fare. Additionally, some "non-genre" influencers in our sample were still adjacent (for example, a strategy or survival game channel might still attract RPG players). The finding highlights that genre alignment alone did not confer a strong advantage in this campaign. The game's concept possibly had cross-genre appeal (e.g., an open-world RPG might also intrigue fans of open-world action or adventure genres). Therefore, limiting outreach only to genre-specific channels might not have significantly changed the outcome – broader outreach was about equally effective. Both genre-fit and off-genre content translated views to wishlists at roughly the same efficiency in our regression.

C. Quadrant Segmentation (Combined Indie & Genre): In Model C, we introduced three YouTube exposure variables: both-fit (indie+genre), indie-only, and genre-only (no "neither" category was present among major influencers). The coefficients here provided nuanced insight:

- The Both-fit (Indie & Genre) group had the highest point estimate at ≈ 0.087, meaning these influencers' views were associated with ~0.087% more adds per 1% view increase. However, this came with a large standard error (~0.05) and was only marginally significant (p ~0.08). This indicates a likely strong effect but also high uncertainty, probably because only one or two influencers fell into this category (e.g., MortismalGaming was one such both-fit influencer covering indie RPGs, and our data on them was limited). The confidence interval for this coefficient was wide, so while the point value hints that "ideal fit" influencers could be especially potent, we can't confirm it with statistical reliability.

- The Indie-only group had a coefficient around 0.0556 (SE ~0.019, p = 0.0036), and the Genre-only group had 0.0525 (SE ~0.011, p = 2.6e-06). Both were significant and notably, their values are very close to each other (and similar to what we saw in models A and B individually). This again reinforces that indie-only and genre-only influencers performed comparably in driving wishlists.

- What about the "Neither-fit" category? In practice, none of the top contributing influencers were neither-fit, so this category wasn't explicitly in the model. Essentially, we lacked data on truly out-of-niche influencers because it seems those types did not cover the game (which makes sense – if someone is neither into indies nor the genre, they likely ignored the game). So, we cannot say how a completely incongruent influencer would perform, since that scenario didn't occur in our sample.

Model comparison and congruence effect robustness: Introducing congruence segmentation did not dramatically improve model fit in terms of R^2 or AIC/BIC. In fact, the congruence models had slightly lower in-sample fit than the baseline model (as noted in 4.1) and higher BIC. This suggests that as predictors, splitting by fit vs non-fit did not capture substantially more variance than treating YouTube as one whole. In other words, any differences in effectiveness between those groups were not large enough to greatly reduce the error of the model. Moreover, the lack of statistically different coefficients implies that our data does not provide strong evidence that congruence moderates the impact of influencer coverage in a meaningful way.

We also must consider **limitations** that could have influenced these null findings:

- Sample size & Power: We effectively had at most ~10 distinct influencer "data points" on YouTube in the base model, and splitting them into groups yields even fewer per group. The fact that both-fit had one major influencer means its estimate is noisy. With only 160 days of data and relatively collinear marketing bursts, the power to detect moderate differences was limited. A small true difference might exist but remain undetected.

- Multicollinearity: Even though we segmented by congruence, the exposure variables are still correlated (when one type of influencer posts, sometimes others do too around the same events). This can inflate standard errors and obscure differences.

- Classification granularity: Our binary classification might be too coarse. For example, not all "non-indie" influencers are equal – some might be slightly into indies, others not at all. Same for genre. A continuous measure of fit or audience overlap could potentially reveal a trend that a binary split misses.

- Twitch not segmented: We only tested congruence on YouTube. It's possible congruence matters more on platforms where audience trust is a bigger factor. Twitch wasn't decomposed by streamer, so any potential congruence effect there (e.g., maybe an indie-friendly Twitch streamer would convert better) couldn't be analyzed.

- Context: All influencers considered were gaming-focused to begin with (we didn't have a lifestyle or non-gaming influencer promoting the game, obviously). So even our "non-fit" influencers were at least contextually relevant (gaming domain). The congruence theory might be more salient when comparing cross-domain endorsements, which was not the case here.

In conclusion, the congruence analysis found no strong moderating effect of influencer–product fit on immediate wishlist conversion rates. Indie-focused and genre-focused influencers were certainly effective, but so were generalists; the data does not show a statistically significant superiority for aligned influencers in driving wishlists. The one category that might have outperformed (both indie+genre fit) is suggested but not confirmable due to data limitations. Adding the congruence segmentation did improve the holdout predictive power of our model (by preventing overfitting to individual influencers), but it did not substantially change the interpretation of which exposures drive results. Therefore, H6 is not supported: we find no statistically significant differences between congruence-defined YouTube exposure coefficients (Wald tests are non-significant).

Whether an influencer was a "fit" or not, if they covered the game, they generated interest. This is an important finding for indie game marketing: it implies that you don't necessarily have to restrict outreach only to niche influencers; broader influencers can be just as valuable in generating wishlists, at least for a game with broad appeal. Of course, this comes with the caveat that all our influencers were still in the gaming sphere – fit might matter more when considering influencers outside the core domain or when a product is very niche.

4.5. Discussion and Implications

4.5.1. Interpretation considering theory

The results of our MMM analysis, including the congruence investigation, offer several points of contact with existing marketing theory on influencer effectiveness. First, our overall finding that influencer marketing significantly drives consumer action (wishlists, in this case) reinforces the growing consensus that influencers can play a critical role in the marketing mix. The Persuasion Knowledge Model (PKM) posits that consumers are wary of overt marketing and will scrutinize the source's credibility and motives. In our context, influencers act as persuasive messengers for the game. One might expect that an influencer who is a better "fit" with the game would be seen as more credible or authentic, thereby reducing the audience's persuasion knowledge (skepticism) and increasing impact. However, our congruence results did not show a large advantage for fit influencers.

This could suggest that source credibility was generally high for all gaming influencers involved. It's likely that viewers perceived even the "non-indie" or "off-genre" influencers as credible sources about the game, perhaps because these influencers maintain reputations for honesty or quality content regardless of specific niche. Prior literature indicates that when influencer–product fit is strong, audiences respond more favorably (higher attitude and purchase intention), but if the overall source credibility is high, even a moderate fit influencer can be persuasive. In our case, the influencers were not random celebrities; they were all gamers, and thus their endorsement of a game (even if outside their usual catalog) likely still appeared genuine and relevant to their followers. This aligns with source credibility theory (Ohanian, 1991) which highlights expertise and trustworthiness as key – an influencer known for gaming expertise can transfer that credibility to any game they try.

It's also possible that persuasion knowledge was low across the board here. All YouTube videos were organic content (not sponsored ads), so followers may not have activated their advertising skepticism at all – they saw it as the influencer genuinely trying a new game. According to PKM, when consumers don't detect a persuasion attempt, they process the message more openly. Thus, even an influencer who wasn't an "indie specialist" could generate interest if followers believed they truly enjoyed the game. Indeed, some bigger variety influencers (non-indie-focused) picked up the game of their own accord because it intrigued them, which likely comes off as a strong endorsement. In contrast, if an influencer is clearly paid to promote an unrelated product, congruence would matter a lot more (incongruence would trigger skepticism).

Another theoretical lens is the match-up hypothesis from celebrity endorsement literature, which suggests that endorsements work better when there is a fit between the endorser's image and the product (e.g., an athlete endorsing sports gear). We attempted to test a similar principle with indie/genre fit. Our null results don't necessarily refute the match-up hypothesis; rather, they indicate that within the relatively homogeneous category of "gaming influencers endorsing a game," the variance in fit might not have been large enough to evoke differential consumer responses. All our influencers match the product category (digital games) to some extent, so the baseline match level is high. The incremental fit of being an "indie guy" or "RPG expert" may be a subtler nuance that, in practice, did not drastically change viewer behavior in this scenario.

Interestingly, we did observe that the double-fit influencers (indie + genre) had the highest point estimate for effect, albeit not statistically firm. This is directionally consistent with theory: those influencers had both high expertise in the genre and alignment with indie culture, so their audiences likely saw them as especially credible recommenders for this game. It's plausible that if we had more data on such cases, we might detect a significant advantage, echoing the idea that when an influencer's personal brand aligns perfectly with the product (high influencer–brand fit), effectiveness is maximized. Studies have found that strong influencer–brand fit can mitigate audience skepticism and bolster persuasion. In our limited sample, the trend supports this, but we caution that it's an insight to be explored further rather than a confirmed result.

Additionally, the effectiveness of press articles in driving wishlists ties into notions of information credibility and authority. Press outlets can be seen as expert sources or "opinion leaders" in their own right. From a consumer behavior perspective, an editorial (earned media) carries weight because it's perceived as independent. The strong impact of media coverage suggests that third-party validation (reviews, articles) was a key trust signal prompting users to wishlist. This resonates with the two-step flow of communication theory – media influences opinion leaders (or directly consumers) and then cascades. Here, press coverage likely influenced both consumers directly and gave content to influencers to talk about.

In summary, our results, interpreted through a theoretical lens, suggest that influencer marketing worked largely due to overall source credibility and content quality, rather than niche alignment alone. All our influencers presumably had built trust with their audiences (through authenticity and expertise in gaming), enabling them to effectively transfer their enthusiasm for the game to fans (consistent with source credibility and PKM frameworks). We did not find strong evidence that micro-segmentation by niche (indie/genre) significantly altered outcomes, which might imply that within the gaming domain, the general "gamer-to-gamer" credibility is the dominant factor – if an influencer enjoys a game and says so, their followers respond, regardless of whether the game is exactly their usual type. This underscores the importance of influencer quality and sincerity. It also hints that the content of the influencer's message (how well they integrate the game into their usual content style) could matter more than their prior channel theme – a hypothesis in line with recent literature suggesting message authenticity and informational value trump simple category fit.

4.5.2. Channel Dynamics Over Time

Our analysis sheds light on how different marketing channels play out over time, revealing **burst vs. sustain patterns** and the importance of timing (adstock effects):

- **Burstiness and Lags:** Channels like YouTube, Reddit, and Twitch showed very burst-driven impacts. The adstock half-life for YouTube was estimated at ~1.3 days, meaning the bulk of a video's impact on wishlists occurs on the day of upload and the day after. This indicates that interest generated by influencer videos is quite immediate – gamers see the video and quickly decide to wishlist if interested. The implication is that YouTube content leads to quick spikes in traffic. Reddit's half-life was even shorter (~0.6 days), suggesting that a Reddit thread's influence is largely confined to the day it trends. People reading the thread will act (or not) in that short window, and by the next day the discussion might be old news. Twitch, as we set, had effectively no next-day carryover; live streams drive concurrent action (viewers wishlist during/just after the stream if at all), but there's little residual effect the following day (unless recorded highlights migrate to YouTube). These findings align with intuitive channel characteristics: social media buzz is ephemeral and needs continuous feeding. The corollary is that marketing via these channels may require a cadence of frequent "bursts" – e.g., multiple influencer videos spaced over weeks – to maintain momentum.

- **Synergies and Timing:** The data revealed that maximal impact occurred when multiple channels' bursts were synchronized around events. For example, during the demo week, we saw simultaneous peaks in YouTube (influencers making demo videos), Twitch (streams of the demo), Reddit (discussion about the demo), and Press (articles reviewing the demo). This temporal alignment likely has multiplicative effects – a user might see the game mentioned on Reddit and YouTube on the same day (reinforcing interest). Our model is linear and can't fully capture synergy, but one can infer it from the large spikes. The takeaway for campaign planning is that coordinated multi-channel bursts around key beats (like a demo) can create a viral feedback loop, hitting the audience from all sides at once.

- Baseline Trend: We included a linear trend which came out positive in most models (though modest, e.g., in congruence model trend coefficient ~0.0065, $p<0.001$). This suggests an underlying organic growth of interest (~0.65% increase in daily adds per day, all else equal). Likely as time went on and the game's release drew nearer or more content accumulated, more people gradually found and wishlisted it. Part of this could be due to word-of-mouth accumulation (friends telling friends, not captured by our channels) or algorithmic amplification (Steam's recommendation engine slowly picking it up). It's a reminder that not all growth comes from measured media – there is a baseline building of hype possibly from community engagement (Discord, minor forums, etc., not in our model) and increasing credibility as more wishlists themselves push the game up charts.

- **Seasonality and weekly rhythm:** As noted, more wishlists occurred on weekends even after controlling marketing. This points to the rhythm that player engagement is not uniform across time – releasing content on a Friday or Saturday might naturally yield better results than on a Monday. So timing bursts to when the audience is most receptive (weekends, holidays) can amplify effectiveness.

In essence, our results portray an environment where marketing impact decays quickly, requiring a steady drumbeat or well-timed surges to maintain attention. They also highlight the importance of aligning marketing with product events (demo) and external cycles (weekends) to maximize efficacy. An implication for marketers is to plan the marketing calendar such that big content drops are sequenced (not all on one day then silence, but waves of content) – e.g., influencer videos in week 1, a Twitch event in week 2, etc., to keep the adstock "topped up" and not let interest fully decay. Conversely, when a major beat like a demo is coming, stacking many channel efforts in that window can create a "perfect storm", knowing that after the peak, decay will happen and that's acceptable if one has another beat later. Our findings reinforce classic advertising principles of flighting (bursts of ads) vs. pulsing – in the digital influencer context, a pulsing strategy (regular small bursts) might sustain baseline interest, with occasional flights (big bursts) for major events.

4.5.3. Managerial Implications

From a practical marketing standpoint – especially for indie game developers and marketers – several actionable insights emerge from this study:

Invest in Influencer Marketing – Broadly: The analysis clearly shows that influencers (YouTube and Twitch) and community channels (Reddit) drove large portions of wishlist additions. For an indie game with limited budget, these earned media channels offer high ROI (since we didn't even account for cost, but all of these exposures were essentially free). Managers should prioritize building relationships with content creators. Our findings suggest not to overly narrow the focus to only "perfect-fit" influencers: even general gaming YouTubers can deliver strong results. It may be beneficial to cast a wide net among gaming influencers who show genuine interest in the game, rather than only targeting those whose brand exactly matches the game's niche. The lack of a significant congruence penalty implies you shouldn't fear reaching out to a bigger variety streamer or a general gaming channel – if they like the game enough to cover it authentically, their audience can be activated. That said, one should still ensure the influencer's community is generally aligned with gaming (which in our case, all were). We wouldn't extrapolate this to say any random celebrity would work – domain relevance is still key. But within the domain, be inclusive of mid-sized and large influencers even if they aren't known as "indie gurus," as long as the content resonates with them.

Leverage High-Impact Events (Demo/Betas): One of the most striking outcomes was the outsized impact of the free demo. For marketing managers, this underscores that product-led marketing events (free demos, open betas, free weekends) can yield returns that dwarf months of standard marketing. If feasible, incorporating a demo or early access period into the pre-launch campaign is highly recommended. However, to maximize it, it should be coordinated with marketing: our case worked so well because the demo wasn't dropped in isolation – it was accompanied by press outreach ("Press kits went out to ensure articles on demo launch day") and creator engagement (inviting YouTubers/streamers to play the demo immediately). The implication is to treat a demo launch like a major campaign launch, synchronizing all channels to it. Ensure press releases, social media buzz, and influencer partnerships are all lined up when the demo goes live, to hit that multiplicative effect. Similarly, if doing a limited playtest or beta, hype it up and perhaps encourage participants to share (if allowed), since even a modest closed event gave us a boost. In short, product events not only directly convert players but also provide fresh content for media to talk about – use them as focal points of the marketing calendar.

Channel Mix Optimization: The relative contributions of channels can guide where to put effort in future campaigns. YouTube and Press were nearly equal top contributors (~40% each of modeled impact), Reddit next (~22%), then Twitch (~10%), with TikTok negligible or negative. For an indie PC game, this suggests focusing on YouTube content creation and press outreach as primary pillars. Concretely:

- Allocate significant time to courting YouTube creators (both big and small) – provide them early keys, exclusive content, or simply network to get them interested.
- Put effort into PR: reach out to gaming journalists and websites, prepare story angles (especially around key milestones like demo, new trailers, etc.). The data shows a single article on the right outlet can have a huge ripple effect.
- Cultivate Reddit presence carefully. While you can't force something to go viral on Reddit, you can engage authentically on relevant subreddits (post dev diaries, respond to comments) to seed discussion. We saw Reddit can amplify interest significantly if the community latches on to a narrative or comparison. Managers should identify key subreddits (r/Games, r/IndieGaming, genre-specific subs) and become a part of those communities early, so that when there's big news, the community is primed to respond.
- Twitch might be slightly less central for pre-release indie marketing unless you have streamers on board. Our results suggest Twitch's impact, while positive, was smaller – possibly because the game might not be as entertaining to stream or fewer stream-

ers covered it. That said, Twitch should not be ignored – it still contributed meaningfully, so inviting a few streamers to play early builds can build grassroots hype.

- De-prioritize TikTok (for similar indie PC titles), or rethink its strategy entirely. If resources are limited, focusing on the proven channels (YouTube, press, Reddit) might yield better ROI than trying to crack TikTok for a PC RPG. However, this might differ for a game targeting a younger/mobile audience. Managers should always consider platform–audience fit; in our case, it seems TikTok's user base wasn't the ideal target for Steam wishlists. The time spent making TikTok content could perhaps have been better spent making a dev vlog on YouTube or an AMA on Reddit.

Timing and Coordination: We recommend a pulsed marketing schedule leading up to launch. Because interest decays, do not exhaust all marketing in one early burst. Our data showed consistent baseline adds but big spikes when events happened. A tentative strategy could be: Month 1 – teaser and initial press article; Month 2 – closed playtest with select community (generate word-of-mouth); Month 3 – first big YouTube push (reach out to influencers to drop videos in a coordinated week); Month 4 – Steam demo + Next Fest participation (major multi-channel push: press, many influencers, streams); Month 5 – continued drip content (weekly small updates on socials, maybe a second wave of influencer mini-content); Launch – final press reviews and streaming marathon. Such a staggered plan ensures there's always something to keep the game in conversations, leveraging the short-term spikes of each channel and not leaving long gaps where momentum could zero out.

Influencer Selection & Relationships: Even though we didn't find statistically different performance by influencer type, one managerial implication is that relationship building and authenticity are key. It may be that the influencers who chose to cover the game did so because they found it genuinely interesting. Ensuring your game is presented compellingly so that influencers want to play it is critical – in other words, the best results come from earned influencer coverage, not paid plugs. Thus, focus on creating a pitch or experience that excites influencers (e.g., a unique demo, or offering them direct access to the devs, etc.). Also, consider mixing influencer sizes: large generalists gave reach, while smaller indie-focused ones gave depth of engagement – having both covers your bases.

Community Engagement: The Reddit effect highlights community engagement as a marketing function. Developers or community managers should engage sincerely on community forums. Hosting an AMA on Reddit around a milestone could be very beneficial (we saw some Reddit spikes likely from such interactions). Similarly, maintaining a presence on Discord or other hubs can turn players into advocates who then propagate excitement on social platforms.

Monitor & Adapt: Each channel's contribution can vary by campaign, so marketers should track their own metrics and perhaps run smaller tests (e.g., see if a TikTok post has any UTM-tracked impact on Steam page visits). MMM analysis like ours can be done periodically (if data allows) to recalibrate efforts. If one sees, for example, that a particular influencer drove an exceptional conversion rate, that's a signal to double down on that influencer or similar profiles (even if our general analysis didn't show a broad pattern, individual differences exist – e.g., maybe one non-fit influencer did as amazing as fit ones because of personality or video style). Thus, combining the aggregate learnings with specific performance insights (like creator-specific referral data) would optimize the mix further.

In sum, for marketing managers in the indie game space, the recommendation is to embrace influencer and community marketing as core tactics, strategically time big pushes around playable content, and not to overly silo the outreach (include a diversity of influencer types). The goal is to generate sustained buzz that peaks at key moments, leveraging the low-cost, high-authenticity nature of these channels rather than solely relying on paid advertising (which we did not analyze here, but typically for indies, paid ads are less effective compared to organic hype).

5 | Conclusions and future developments

This thesis examined the marketing mix of an indie video game during the pre-launch period, with a specific focus on influencer-driven and earned media channels. The empirical analysis applied an MMM-inspired time-series regression framework where daily Steam wishlist additions ("Adds") were modeled as a function of daily marketing exposure levels across YouTube, Twitch, Reddit, TikTok, and Press/Media, while controlling for trend, day-of-week effects, and major product events (Demo release and Playtest).

Overall, the results support the view that influencer marketing and earned media are central drivers of pre-launch demand in the indie game context. In the aggregated model, YouTube, Twitch, Reddit, and Press/Media exposures were associated with statistically significant positive effects on wishlists, indicating that increases in attention and third-party visibility translate into measurable increases in consumer intent. Press/Media coverage emerged as a particularly influential driver, consistent with the role of editorial credibility and broad reach in shaping awareness and interest. In contrast, TikTok exposure did not show a positive contribution in this case study and, depending on model specification, it appeared either weak or negative, suggesting that platform–audience fit may be a critical boundary condition for short-form channels in a Steam pre-launch setting.

Beyond continuous marketing activities, the analysis highlighted the disproportionate importance of product-driven events. The Demo release produced a large discontinuous lift in daily wishlist additions, far exceeding typical day-to-day changes explained by channel exposures. The Playtest event also showed a positive lift, albeit smaller in magnitude. These findings reinforce a practical interpretation: in indie game marketing, major playable milestones can act as catalysts that amplify both organic discovery and the effectiveness of concurrent communication activities.

A further objective of the thesis was to test whether influencer–product congruence moderates the effectiveness of influencer marketing. Congruence was operationalized through two binary dimensions (“indie fit” and “genre fit”), and YouTube exposure was segmented by these groups. The congruence models, while slightly less accurate in-sample than the simplest aggregated model, provided stronger out-of-sample stability than the highly decomposed influencer-level model. In substantive terms, the results did not provide strong statistical evidence that congruent influencers systematically outperform less congruent influencers in converting exposure into wishlists within this dataset. This suggests that, within the broad and already domain-relevant category of gaming influencers, general source credibility and content relevance may dominate over narrower niche alignment. At the same time, the analysis indicates that theory-driven grouping can be a useful way to reduce overfitting and improve model robustness when only a single-game, short-horizon dataset is available.

Academic contributions

This thesis provides three main academic contributions. First, it demonstrates the feasibility of extending an MMM-style framework to non-traditional, exposure-based measures that reflect influencer marketing and earned media rather than only paid media spend. By combining log transformations, adstock dynamics, and time-series controls, the study provides an interpretable approach to quantify how digital attention proxies relate to an actionable pre-launch KPI. Second, the thesis contributes to the emerging discussion on marketing analytics for the indie gaming industry by applying a rigorous, transparent modeling framework to a data-scarce, event-driven market context where standard long-horizon MMM assumptions are often violated. Third, it proposes and tests an operational approach to influencer–product congruence within an econometric marketing effectiveness model, linking influencer marketing theory (fit and alignment) to measurable differences in channel effectiveness, and highlighting both the potential and the limitations of such moderation tests in small samples.

Managerial implications

Managerial implications for indie game marketers are discussed in detail in Section 4.5.3. In summary, the evidence suggests prioritizing YouTube content, community discussion channels such as Reddit, and press outreach, especially around major product milestones. The outsized impact of the Demo release indicates that playable assets can be among the most effective “marketing levers” when coordinated with communication bursts across creators and media. Finally, the mixed results for TikTok suggest that marketers should not assume cross-platform transferability of effectiveness and should evaluate audience fit and funnel alignment when allocating scarce resources.

Limitations and future developments

This study is based on a single-game case study and a limited observation window, which naturally constrains external validity. Several measurement choices were driven by data availability (e.g., using public exposure proxies and simplified measures for certain platforms), and endogeneity concerns cannot be fully eliminated in observational time-series settings.

Future research can build on the proposed framework in multiple directions. A first extension is to expand to multi-game or multi-campaign datasets, enabling hierarchical modeling and stronger statistical power for testing heterogeneity across influencer types and congruence levels. A second extension is to improve exposure measurement and granularity, particularly for live streaming, by collecting streamer-level metrics when available. A third direction is to enrich the modeling of earned media and community dynamics by incorporating content characteristics (e.g., sentiment, topic, or engagement quality) and by exploring interaction effects across channels and events. Finally, linking pre-launch wishlists to post-launch sales outcomes would enable a full-funnel validation of the KPI choice and would allow direct ROI comparisons across channels.

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A | Appendix

The following appendix presents the extraction and organization of key data from the "Ardenfall Master Wishlists" dataset. This dataset covers daily game-metric records from 5 August 2025 to 11 January 2026, tracking user engagement and visibility metrics. We have identified relevant variables (wishlists additions, page visits, social media views, etc.) and created structured tables for inclusion in a thesis. Tables include dataset metadata, descriptive statistics, variable definitions, and data-cleaning examples.

A.0.1. Descriptive Statistics

Table A.1 presents the same statistics in a long format (one metric per row). This format is useful for listing many variables. "New Wishlists" is the net change (adds minus deletes).

Table A.1: Descriptive statistics of main metrics (long format)

Metric	*N*	Mean	Median	Min	Max
Adds	160	147	72	13	1259
Deletes	160	17	16	2	44
New Wishlists	160	129	52	2	1216
Steam visits (total)	160	983	623	291	6346
Twitch viewers	160	18	0	0	1185
YouTube views	97	3099	414	0	44816
Reddit views	160	3587	0	0	87111
TikTok views	3	1400	900	900	2400

Note: See Table A.2 for definitions. For TikTok, only 3 observations were recorded (late period).

A.0.2. Variable Definitions

Table A.2 lists each variable in the dataset and its description. All date entries were converted to the ISO format (YYYY-MM-DD). Unless noted, values are daily counts of events or views.

Note: Many social/media metrics are estimates. All counts are raw daily totals (unitless). NA indicates missing data (no observation recorded).

A.0.3. Figures

Figures illustrate an example time series from the dataset (daily new wishlists).

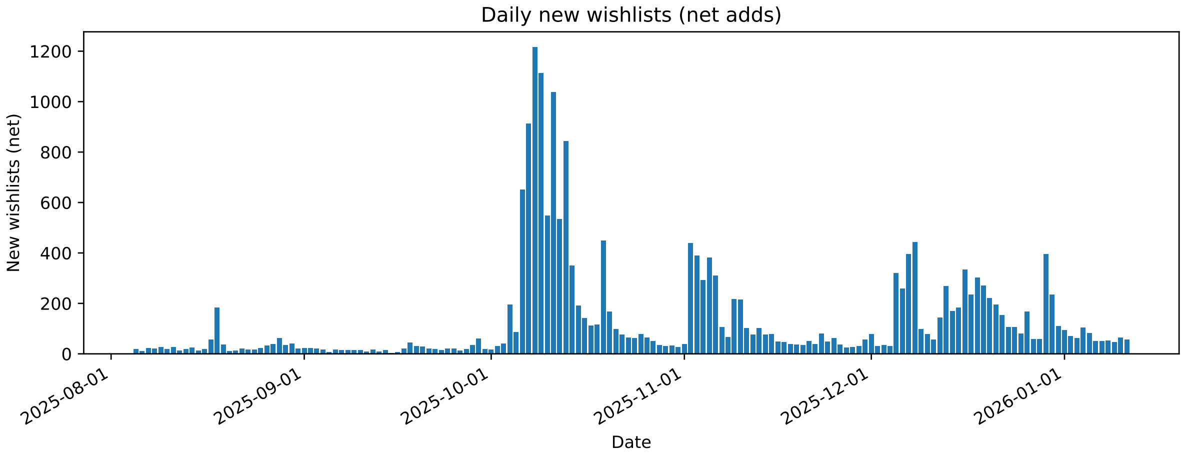

Figure A.1: Daily new wishlists (net adds).

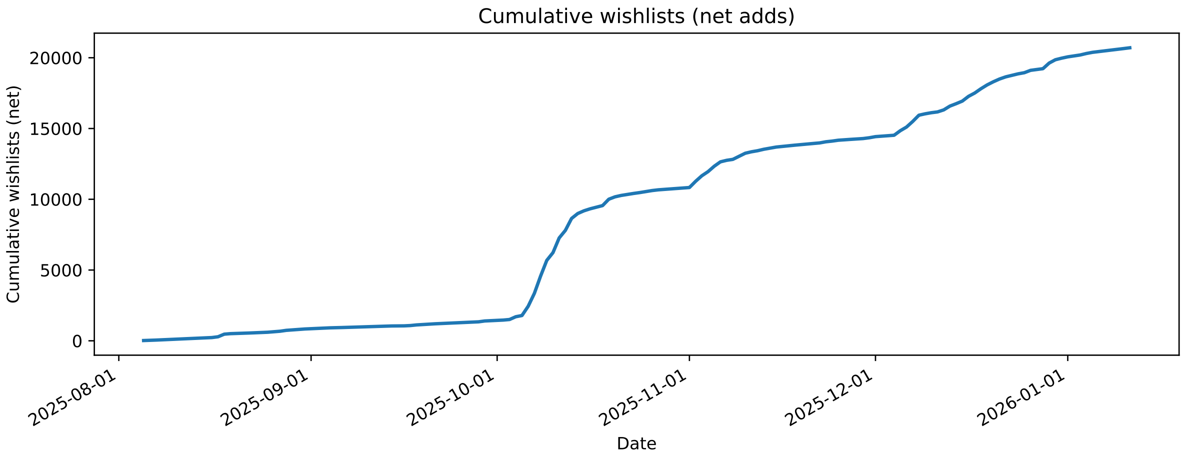

Figure A.2: Cumulative wishlists (net adds).

Table A.2: Variable definitions

Variable	Description
Date	Date of observation (ISO format YYYY-MM-DD)
Adds	Number of users who added the game to their Steam wishlist on that date
Deletes	Number of users who removed the game from their Steam wishlist on that date
New Wishlists	Net new wishlists (Adds minus Deletes) on that date
Steam Page Visits (Total)	Total daily visits to the game's Steam store page
Steam Page Visits (search suggestions page)	Visits via Steam search suggestions
Steam Page Visits (direct navigation)	Visits via direct URL or Steam client navigation
Steam Page Visits (other pages)	Visits from other Steam pages (e.g. front page, publisher pages)
Steam Page Visits (external website)	Visits from external websites linking to the Steam page
Steam Page Visits (wishlist page)	Visits originating from Steam wishlist page
Twitch Viewers	Peak concurrent or total viewers watching Twitch streams of the game (unit unspecified)
YouTube Views Total (reconstructed)	Total daily YouTube views of videos about the game (estimated from comment counts)
Joov YouTube Views	Daily YouTube views on videos by Joov about the game
Coldbear YouTube Views	Daily YouTube views on Coldbear's channel about the game
SplatterCatGaming Views	Daily YouTube views on SplatterCatGaming's videos
JBN YouTube Views	Daily views on JBN's YouTube channel videos
MortismalGaming Views	Views on Mortismal Gaming channel videos
Nookrium YouTube Views	Views on Nookrium's channel videos
JBN Viral Short Views	Views on a viral short video by JBN about the game
Urgie Short Views	Views on Urgie's short video about the game
Sir Schmib YouTube Views	Views on Sir Schmib's video about the game
JampackSam Short Views	Views on JampackSam's short video
Reddit Views (Aug Indie Sunday)	Daily page views from /r/IndieGames (August Indie Sunday event)
Reddit Views (Sept Indie Sunday)	Views from /r/IndieGames (September event)
Reddit Views (Nov Indie Sunday)	Views from /r/IndieGames (November event)
Reddit Views (Dec Indie Sunday)	Views from /r/IndieGames (December event)
Reddit Views (r/Morrowind)	Daily views of a post in /r/Morrowind subreddit
Reddit Views (r/ElderScrolls)	Daily views in /r/ElderScrolls subreddit
Reddit Views (r/Oblivion)	Daily views in /r/Oblivion subreddit
Reddit Views (r/CRPG)	Daily views in /r/CRPG subreddit
Reddit Views (r/rpggamers)	Daily views in /r/rpggamers subreddit

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