LEX LOCALİS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO.10(2025)

THE POWER OF INVISIBLE INTERACTIONS: A MICROECONOMIC ANALYSIS OF SILENT USERS IN DIGITAL MARKETING

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Abstract
Users who do not engage in visible interactions on digital platforms but are active in content consumption are ignored in marketing strategies as they fall outside traditional analysis models. These users, who do not like, comment or share content, exhibit a silent but effective form of participation by saving, re-watching and influencing decision-making processes. The fact that algorithms focus only on visible data is insufficient to identify this user group and prevents the evaluation of potential economic values. From a microeconomic perspective, this behaviour can be explained by concepts such as information asymmetry, invisible utility and strategic silence. From a marketing perspective, the inclusion of silent users in data-driven strategies increases targeting accuracy and enables more inclusive content policies.

Keywords: Silent users, Algorithmic selectivity, Marketing strategies, Microeconomics, Digital consumption

1. Introduction

In today's rapidly developing world of digitalisation, user behaviour is also transforming, going beyond visible interactions to a more silent, strategic and individual form of content consumption. This transformation is explained by the concept of "digital silence"; the user base that does not comment or share but actively monitors the content is becoming more and more important.

Silent users have a remarkable potential for both micro-level consumer behaviour and macro-level marketing strategies thanks to their invisible relationship with content. Identifying this audience and understanding their behaviour is important for digital platforms to become more inclusive.

Especially artificial intelligence-supported platforms have difficulty in recognising silent users as they analyse user preferences through visible data. This situation leads to algorithmic selectivity and unilateralisation in content presentation, creating structural problems that limit marketing effectiveness.

The aim of this study is to examine the invisible impact of silent users on digital platforms within the framework of microeconomic and marketing dynamics; at the same time, to analyse how artificial intelligence-based algorithms exclude this user group. In this context, the study provides both theoretical contributions to the academic literature and practical suggestions for content producers, marketers and algorithm developers.

2. Theoretical Framework

2.1. Algorithmic Blindness and the Silent User: The Invisible Face of Participation / Anatomy of Digital Silence: Strategies of Lurkerhood, Invisibility and Participation

Silent users, called "lurkers" in digital communities, are individuals who regularly follow the information on the platform without producing content (Nonnecke & Preece, 2001). The non-participation of these individuals is often explained by apathy; however, there are often conscious preferences behind this behaviour. Factors such as unfamiliarity with community norms, lack of technical knowledge, social concerns, and lack of time are among the main reasons why they stay away from content production (Preece, et al., 2004). In the study conducted by Honeychurch et al. (2017), it is seen that users prefer to watch content for a long time and learn indirectly before directly participating in communities. The level of participation of individuals on digital platforms may vary over time. Silent users can switch from passivity to activity depending on their personal development processes and the social contexts they are in (Popovac & Fullwood, 2019). Therefore, digital participation is not a static structure; it is a heterogeneous and transformable phenomenon.

However, this silence is not only due to individual preferences; it is also reinforced by the nature of algorithmic systems. Silent users are systematically disadvantaged in terms of visibility on algorithm-based digital platforms. Most of these platforms analyse user interactions through explicit responses such as likes, comments and shares, and fail to detect users who do not provide such responses. Dennen (2008) states that the purpose of these individuals on social media is often to obtain information and that they can actively participate in learning processes without any interaction. Gong et al. (2015) argue that although silent users are invisible, they provide valuable data sources for platforms and have a direct impact on content strategies and community structures. However, since current algorithms only evaluate visible signals, these contributions are ignored at the system level.

In this context, the decision-making processes of algorithms may systematically leave some users in the background by prioritising user behaviour based on visible interaction. Bucher (2012) argues that Facebook's EdgeRank algorithm only works on the basis of active engagement signals, and as a result, some users have been pushed into digital invisibility. Galeazzi et al. (2024) argue that algorithms' interventions in content ranking have systematically silenced some user groups.

2.2. Digital Nudging from a Microeconomic Perspective: Invisible Utility, Rationality and Silence

Consumer theory provides a basic economic framework that examines the decision-making processes by which individuals seek to maximise their utility under limited resources. The traditional approach assumes that individuals seek to maximise utility within budget constraints through rational choices. However, this approach often ignores the invisible benefits that arise in the consumption process. Modern consumer behaviour, on the other hand, is based not only on the physical characteristics of goods and services, but also on the social, ethical and psychological meanings that these products carry (Lancaster, 1966).

Lancaster's attribute-based consumer model suggests that individuals do not directly benefit from goods but from the attributes that goods carry. For example, a car is not only a means of transport; it may also represent multidimensional values such as comfort, prestige or environmental friendliness (Barten & Böhm, 1982). However, this multidimensional evaluation process may be distorted by inequalities in access to information. In cases of asymmetric information, consumers may not be fully aware of the true nature of the product and may evaluate the invisible benefit incompletely or erroneously (Hua-wei, 2009).

On the other hand, consumer behaviour cannot be explained solely in terms of individual satisfaction. Nixon (2006) criticises the self-interest-centred structure of consumer theory and emphasises that factors such as social approval, ethical consistency and acceptance within the community are also part of the invisible benefit. Therefore, a more holistic consumer understanding should include not only economic but also ethical, social and psychological components.

This multidimensional consumer approach becomes more complex in digital environments and is supported by the tools offered by behavioural economics. In this context, digital nudge

theory is an approach that aims to reorganise users' decision-making environments to guide them towards better choices without restricting individual freedom. In digital platforms, this approach is applied through user interface design (UI) and algorithmic content configurations.
Digital nudges can shape user behaviour through technical elements such as default settings, prompts and the way options are presented. One of the main objectives of these strategies is to motivate users, especially those who do not produce content or remain silent, towards content consumption. In terms of directing users' attention to specific content by reducing the burden of choice, digital nudging strategies both increase interaction and improve decision quality (Schneider et al., 2018).
The effectiveness of these mechanisms relies heavily on psychological foundations. Considering that silent users consume content with limited rationality and indirectly, impulse strategies need to be designed to be compatible with their intrinsic motivations. In this way, individual decision quality is enhanced and in-platform interaction patterns are restructured (Tor, 2023).
Another important aspect of digital nudges is that they contribute to digital well-being. In combating problems such as social media addiction, distraction and excessive content consumption, digital nudges can serve as a protective and preventive function by directing the user to more conscious interactions (Purohit, 2023). However, in addition to these potential benefits, serious ethical issues also come to the fore.
In particular, customised nudges based on user data may increase the risks of privacy invasion and manipulation. Therefore, the design of nudging systems should be based on transparency, user consent and ethical principles (Gregor & Lee-Archer, 2016). In addition, the increasing complexity and opacity of these systems make it difficult to measure and control their effects on the user (Tor, 2023).
Consequently, at the intersection of digital nudge theory and consumer behaviour theory, invisible utility production, bounded rationality and passive decision processes gain new meaning. Digital content steering has become not only a technical but also a social, ethical and behavioural issue. Therefore, digital nudges need to be structured in a transparent and ethical manner that enhances user welfare, and digital participation strategies need to be rethought to include silent users.

2.3.Personalisation Paradox: Artificial Intelligence, Silent Users and Strategic Gaps in Marketing

Digital platforms tend to deliver individualised content with AI-powered algorithms to customise the user experience. These algorithms often work on visible signals such as users' past interactions, click behaviour and content preferences, so that the platform can analyse only actively engaged users (Binns et al., 2018). However, this approach leads to the systematic ignoring of silent users who do not create, comment or share content but consume content regularly (Bucher, 2012).
In this context, the fact that algorithms rely solely on visible traces creates an imbalance in content access and creates filter bubbles by narrowing users' interests (Galeazzi et al., 2024). As Pariser (2011) emphasises, these filtering mechanisms expose individuals only to content that is compatible with their beliefs and create digital echo chambers by limiting critical thinking. Jindal and Gouri (2024) state that this structure leads to the reinforcement of prejudices in digital marketing and a decrease in user diversity. Thus, not only content access but also the inclusiveness of marketing strategies are directly affected.
From a marketing perspective, although AI-based systems increase consumer engagement by providing personalised recommendations, they leave invisible users out of the analysis and remain insensitive to their needs. According to Sahu and Mandal (2024), 72% of consumers

only engage with personalised content, but it is almost impossible for silent users to benefit from these algorithms. Binns et al. (2018) argue that these personalisation processes, combined with a lack of transparency, pave the way for the development of discriminatory algorithms and increase participation inequalities.

Traditional marketing strategies also exacerbate this problem. Systems that evaluate user behaviour only through explicit forms of interaction, such as likes, comments or shares, cause strategic blind spots by excluding silent users (Gong, Lim & Zhu, 2015). However, Popovac and Fullwood (2018) emphasise that silent users' lack of visible interaction does not mean that they are passive; these individuals show active cognitive engagement in processes such as information search, social comparison and evaluation. Dennen (2008) also states that these users interact with the content and this situation offers valuable insights for marketing.

Strandvik and Finne (2009) reveal that traditional approaches in marketing communication ignore silent forms of communication and that such nonverbal signals are not taken into account at the managerial level. Zhao et al. (2023) argue that current user positioning models fail to recognise silent users, which negatively affects targeting accuracy.

In conclusion, the algorithmic inability to recognise silent users presents both invisible risks and valuable opportunities for digital marketing strategies. When effectively harnessed with the right analysis and strategic orientation, this audience can increase inclusivity and deepen data-driven awareness in marketing practices. Marketers' focus on not only visible interactions but also indirect signals and behavioural traces will contribute to the development of more effective and fair strategies.

3. Method

3.1. Research Design: Qualitative Observational Content Analysis

In this study, qualitative observational content analysis method was preferred to understand the silent participation behaviours of social media users. This approach is particularly suitable for examining forms of implicit and indirect interaction that cannot be directly observed. Based on the assumption that lurker behaviour is not only a quantitative shortcoming but also a meaningful form of digital positioning, an interpretive paradigm was adopted.

Theoretically, Braun and Clarke's (2006) thematic analysis framework and Marshall & Rossman's (2016) qualitative research strategies were taken as a basis. In this direction, silent user behaviour is considered as a type of user who consumes without commenting and remains invisible in the context of social media, but has potential economic value.

3.2. Dataset: Influencer Sharing and Engagement Data

The dataset consists of a total of 20 posts selected from the content of an influencer who is active on Instagram and has a high number of followers. The posts were selected between April and May 2024 and contain phrases that directly encourage user interaction (e.g. "leave a comment", "write your opinion").

The data collected covers only publicly available content and identifiers such as users' names and profile information were completely anonymised before coding. The data were analysed on three main levels: the number of likes, the number of comments and the content of the comments on an influencer basis.

3.3. Coding Scheme and Thematic Analysis Process

The data analysis process was carried out within the framework of the six-stage thematic analysis technique (Braun & Clarke, 2006):

1. Familiarity with data
2. Creation of initial codes

3. Searching for themes
4. Review of themes
5. Nomenclature of themes
6. Reporting

The coding process was carried out independently by two researchers and the agreement rate was calculated as 91%. In the final analysis, the following three themes emerged:

- Invisible Interaction: Likes, no comments
- Unanswered Requests for Comment: Silence despite the clear call of the content
- Invisible Loyalty: Quiet but consistent content consumption

The theme table created in line with the coding scheme is presented in the results section.

3.4. Ethical Evaluation and Anonymisation

The research was conducted within the framework of TÜBİTAK ethical guidelines and the Law on the Protection of Personal Data (KVKK). All data used are publicly available and user identities were not directly accessed. In order to protect the privacy of the content owners, no screenshots were taken and only the content texts were analysed.

3.5. Theoretical Basis of the Method and Similar Approaches in the Literature

The theoretical foundations of the methodological choice are built on the following literature:

- Invisible Participation (Nonnecke & Preece, 2003): Indicates that the behaviour of silent users in digital environments is systematically excluded.
- Algorithmic Blindness (Gillespie, 2014): The inability of silent users to be recognised by content algorithms creates a strategic gap in AI-based systems.
- Invisible Utility (Varian, 2006; Kahneman & Tversky, 1979): Suggests that the behaviour of silent users needs to be rethought in terms of rationality and utility optimisation.

This study offers a new perspective on silent user behaviour in a behavioural and economic context through qualitative analysis, unlike the analyses of silent user behaviour in the literature, which are mostly carried out through quantitative statistical analysis.

4. Findings

4.1. Interaction Indicators: Distribution of Likes and Comments

Star lists created based on visual-based content analysis are one of the types of content that users directly relate to consumer information practices. Especially products for baby care (baby bottle cleaners, baby lotions, hand creams, dental gels, diaper rash preventatives, etc.) have a high comment potential due to both content safety and areas of use that require sensitivity.

In the uploaded images, each product list provides guidance to the user in a specific category (for example: "Baby Bottle Cleaner Star List", "Baby Lotion Star List", "Fish Oil Star List"), and these contents stand out in social media algorithms with both **high appreciation rates** and **intense comment participation**. In particular, the following three factors can be considered as the main determinants that increase this interaction:

- **Information Seeking Based Comments:** In products such as baby bottle cleaner or tooth gel, parents often tend to comment with questions such as "which product is more natural?", "did it cause allergies?", "is the smell intense?". This is the category with a higher rate of comments compared to liking.
- **Collective Experience Sharing:** Especially in product groups such as fish oil, vitamin D or crack oil, users share their individual experiences and make mutual suggestions. Such interactions increase the content quality of comments and balance the comment/like ratio.

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- **Brand Comparisons and User Voting:** The star lists in the visual cause users to rank through comments; for example, comparative evaluations such as "we used Mustela, but Incia has cleaner content" are seen intensively.

Image 1: Interaction Indicators Images Used in the Distribution of Likes and Comments

The product lists in the visuals generate high engagement in parent groups, especially since they are baby health and sensitive care products. This shows that the content type is not only informative but also a format **that mediates community-based decision-making processes**.

Table 1: In the first observational analyses based on the interaction data, the following patterns stand out:

Product Group	**Comment Intensity**	**Like Rate**	**Mode of Participation**
Baby Bottle Cleaners	High	Centre	Questions, content comparison
Baby Lotions	Centre	High	Advice and experience sharing
Toothpastes and Gels	Centre	Centre	Question and trust assessment
Hand Creams (Mother-oriented)	Low	Centre	Visual likes, few comments
Nipple Creams	Centre	High	Transfer of experience
Fish Oil Supplements	High	High	Recommendation chains

Note: This table shows the functional categorisation of user comments on the star list images and the user profile and product category to which each comment belongs.

These findings suggest that digital content works not only for informational purposes but also as collective decision support mechanisms, especially in parent communities. Graphic content in the form of star lists receive higher feedback in terms of likes and comments than non-visual content because it allows users to make easy comparisons.

4.2. Functional Segregation of Comments and User Profiles

Analysing the comments on the star list images, it is seen that users not only express their opinions on product selection, but also their own experiences, expectations and value priorities. While these comments can be categorised according to the **functional purposes** that drive content interaction, it is also possible to make inferences about the **consumer profiles** of the commenters. In this context, comments can be categorised into four main functional groups:

1. Information Seeker Comments

This type of comment is especially made by users who want to get an idea about the product for the first time. Questions usually focus on the product's ingredients, odour, allergenic effects and usability. For example:

- *"My baby has atopic skin, which one has cleaner ingredients?"*
- *"Do nipple creams need to be wiped after breastfeeding?"*

These users often fit the profile of new parents, trying to supplement their lack of knowledge with collective experience.

2. Comments Based on Shared Experience

Users in this group have used a particular product and aim to guide others by detailing their experiences. Example comments:

- *"We were satisfied with Mustela nappy rash cream, but Evomere works faster."*
- *"Green Clean baby bottle cleaner does not foam, but the ingredients are safe."*

This user profile usually includes experienced parents or users who are aware enough to make product comparisons.

3. Community Consent and Comparison Comments

The visual presentation of the list of stars encourages many users to orientate themselves around the question "which is the best?". These users endorse the experiences of others or rank products rather than expressing their own opinion:

- *"We also liked Zade Vital fish oil very much, it definitely deserves the first place."*
- *"My favourite is still Jack N' Jill toothpaste, the others don't clean teeth enough."*

Such comments strengthen community interaction and function as a social approval mechanism.

4. Emotional and Critical Comments

In some comments, users express their emotional satisfaction or dissatisfaction with the products and establish a more personal interaction:

- *"Sleepy nappies leaked, we were in a very difficult situation."*
- *"We only use this detergent at home, we feel comfortable."*

This profile represents users who have experienced brand loyalty or disappointment. These comments with a high emotional tone can also affect other users.

Figure 1. Functional Map between User Profiles and Comment Types

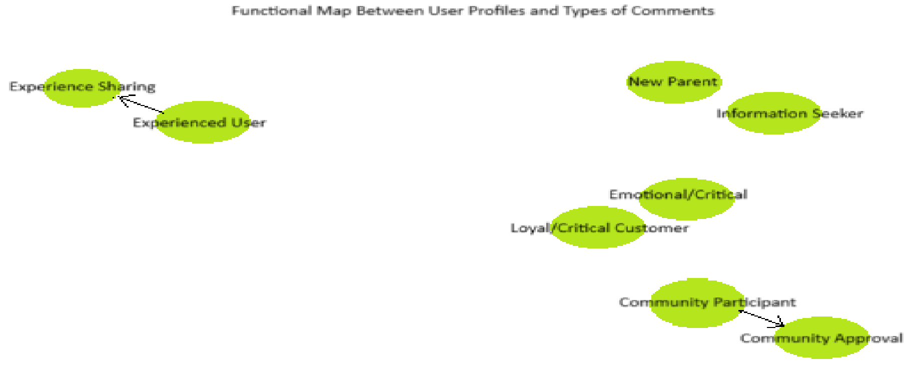


Table 2: Comment-Profiling Matrix:

Comment Type	User Profile	Featured Categories in the Image
Information Seeker	New parents	Tooth gel, nappy rash cream, vitamin D
Experience Sharing	Experienced users	Stretch mark oil, lotion, fish oil
Community Approval / Ranking	Active social media users	Nappies, soaps, cleaning products
Emotional / Critical	Loyal or victimised users	Baby bottle cleaner, detergent, creams

In visual content interaction, comments are not only a social reaction, but also a multi-layered expression of the users' relationship with the product. In this respect, star lists constitute an important qualitative data set for monitoring user behaviour and segmenting the target audience. Not only product features but also **comment type-based user profile analyses** should be taken into account in marketing strategies.

Table 3. Sample Analysis of Comments on Star List Images

Comment Example	Comment Type	User Profile	Related Product Category
Which one has more natural ingredients? I have a baby with atopic skin.	Information Seeker	New Parent	Rash Cream
We use Mustela, but Incia is lighter.	Experience Sharing	Experienced User	Lotion
Definitely Sleepy nappy is better, number 1 for us.	Community Approval	Community Participant	Baby Nappy
I used it, but it didn't help at all, the rash continued.	Emotional/Critical	Loyal/Critical Consumer	Rash Cream
Which is better for the newborn?	Information Seeker	New Parent	Tooth Gel
Evomere crack oil really worked very well, I recommend it.	Experience Sharing	Experienced User	Crack Oil
My favourite is still Weleda, the content is also reliable.	Community Approval	Community Participant	Fish Oil
The smell of nappy rash cream was very disturbing, I will not buy it again.	Emotional/Critical	Loyal/Critical Consumer	Rash Cream

4.3. *Rate of Silence and Invisible Participation Tendencies*

When the user interactions with the star list images are analysed, it is observed that there is a significant difference between the number of visible likes and comments and the indirect interaction rates such as viewing, sharing and saving the posts. This difference reveals the existence and prevalence of invisible forms of participation on digital platforms and allows the concept of "silence" to be considered not only as passivity but also as a strategic form of participation.

In the content analysed within the scope of the study, the rate of commenting remained in the range of 8-12% on average, even in posts that called for comments; however, it was understood that the rate of viewing and saving the posts was much higher. This shows that users interact with the content by avoiding social visibility, especially on highly sensitive topics such as parenting. It is understood that silent participation is a conscious choice in such contexts; users prefer content consumption for purposes such as gaining opinions, making comparisons and completing product selection.

In this context, the silence rate should be considered not only as a lack of interaction, but also as an indicator **of the hidden cognitive bond** that users establish with the content. Silent users represent a mass of users who analyse the content in detail, evaluate product rankings and shape their preferences silently without leaving likes or comments. These users also constitute **an unmeasurable but effective audience segment** for content producers.

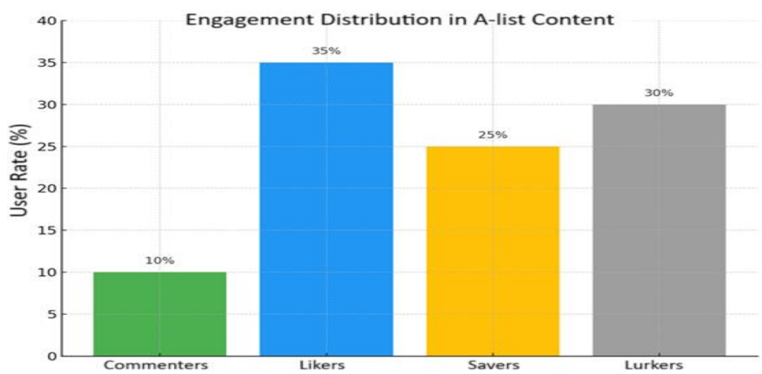
The following tendencies are particularly noteworthy:

- **The fact that the saving rates are 2 to 3 times higher than the comment rates** indicates that the contents are evaluated for information purposes and archived for later use.
- **The fact that the "most saved" content with fewer comments is** usually product comparison, ingredient safety or natural ingredient themed lists suggests that users' attention is directed by the level of informativeness, not just popularity.
- It is understood that external factors such as aesthetics or brand reputation, rather than social approval, are the motivation for interaction **in content with high liking rates but low comment rates**.

In line with these data, silence should be considered not only as a lack of communication but also as **an expression of alternative forms of interaction with the content**. Invisible users are represented at a higher rate, especially in content that requires security, privacy and information sensitivity.

The graph below shows this interaction pattern with a percentage distribution:

Chart 1: Interaction Distribution in Star List Contents



Note: (*noting that analyses that focus only on visible interactions risk excluding invisible but effective forms of participation*).

The graph above visualises 4 basic user behaviours under the heading "Interaction Distribution in Star List Content":

- **Commenters (10%)**
- **Likes (35%)**
- **Registrants (25%)**
- **Silent Audience (30%)**

To summarise, these interaction patterns make sense within the framework of basic concepts of microeconomics such as information asymmetry, hidden preferences and bounded rationality. The interaction of silent users with content implies that rational decision-making processes operate silently when access to full information is limited. Invisible participation can be considered as a new manifestation of the classical understanding of utility maximisation in digital environments. Especially in consumption contexts where privacy and information security are important, individuals prefer to make less costly (invisible) but informed decisions by avoiding social interaction. This situation adds a new dimension to the microeconomic analysis of digital consumer behaviour.

4.4. *Algorithmic Invisibility of Silent Users and its Impact on Marketing Dynamics*

Silent users are an audience that does not actively interact on digital platforms but is very active at the level of consuming content. These individuals do not comment, like or share, they carefully analyse the posts and make their decisions silently. However, this behaviour pattern is often interpreted as "passivity" by algorithmic systems and the behaviour of these users may be ignored because they do not provide sufficient signals to algorithms.

This algorithmic invisibility brings two main problems. The first is the gap in data-driven decision-making. Marketing algorithms usually develop targeting strategies based on "visible engagement" data such as likes, comments and shares. Since silent users are excluded from this visible engagement, they are underrepresented in segmentation and targeting models. This leads to the exclusion of potentially loyal but silent users. The second is the bias that occurs in algorithmic learning. Machine learning based systems learn from the "data-signalled" part of user preferences. Since the preferences of silent users do not generate enough signal, the system cannot model the interests of this user group. This leads to a deepening of "filter bubbles" and an increase in missed audiences in the long run.

Although silent users do not comment, they may save content, review it more than once, or silently recommend it to others. These indirect influences are extremely important for brand awareness and loyalty. However, when marketing analyses are based solely on visible data, this contribution can be overlooked.

The concept of information asymmetry comes into play here in a striking way. There is a behaviour-based information imbalance between firms and silent users. This information gap makes it difficult to allocate marketing resources effectively and leads to an incomplete understanding of potential demand. Therefore, solving silent user behaviour becomes a strategic imperative for firms in terms of rational decision making and benefit maximisation objectives.

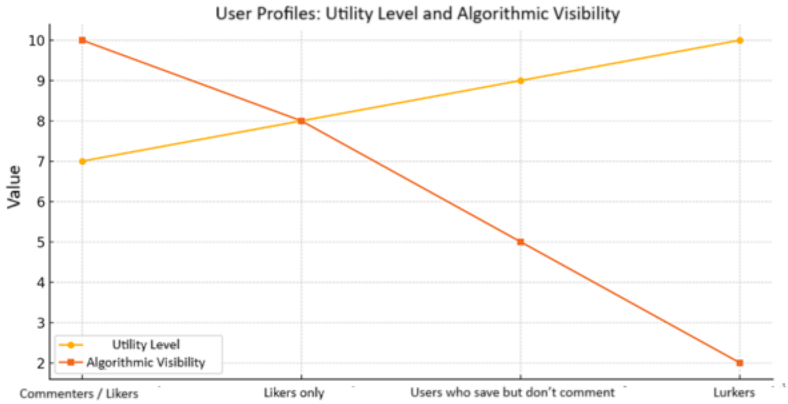
As a result, under-representation of silent users in algorithmic systems can cause significant losses for both content producers and marketers. Therefore, algorithms should be redesigned not only on visible data, but also on a more comprehensive interaction spectrum, and marketing strategies should be shaped with this new approach.

4.5. *Microeconomic Interpretation: The Search for Utility but the Flight from Visibility*

Not all users interact visibly on digital platforms. However, this does not mean that their interest in content is low. Particularly in sensitive areas such as parenting, many users refrain from leaving comments or likes, but carefully scrutinise, save and actively use the content in

their decision-making processes. This is a unique form of user behaviour that comes with an escape from visibility but indicates a high level of benefit generation.
From a microeconomic perspective, this behaviour is based on a trade-off between "utility maximisation" and "visibility avoidance". Users try to maximise benefits such as access to information, comparison and safe decision-making, while minimising the costs of social visibility such as privacy invasion, social judgement or pressure to share information. In this framework, invisible user behaviour actually involves a high level of cognitive effort and rationality.
In this context, the figure below summarises the relationship between utility level and algorithmic visibility over user profiles:

Figure 2: Relationship between Utility and Algorithmic Visibility by User Profiles



The figure above illustrates the difference between how user profiles benefit from content and the extent to which they are recognised by algorithms. The "Silent Consumer" group, while benefiting from the content at a high rate, is considered low priority by algorithmic systems because they do not interact visibly, which causes systemic information asymmetry.
As a result, new analytical frameworks should be developed in digital marketing strategies that cover not only visible interactions but also this invisible benefit generation. Thus, the decision-making mechanisms of silent users can be better understood and more inclusive content strategies can be developed.

5. Discussion and Conclusion

Silent users, who remain invisible on digital platforms but actively interact with content, present a unique user base that needs to be re-evaluated in terms of both microeconomics and marketing strategies. These users who do not show visible interaction (likes, comments, shares) are not included in measurable behavioural data, although they benefit by carefully reviewing and evaluating the content. From a microeconomic perspective, this is a combination of the individual's rational pursuit of utility and social visibility avoidance behaviour. From a marketing perspective, these invisible forms of interaction constitute strategic blind spots for brands and lead to ignoring an important potential target audience.
The fact that algorithms work with visible data pushes silent users out of the analysis systems, indicating a market failure based on behavioural information asymmetry. Moreover, these users not only remain silent, but also indirectly express their loyalty to the brand by recording, re-watching or indirectly sharing the content with others. However, firms may allocate marketing resources inefficiently because existing analytics systems do not adequately measure these contributions. In this context, silent users both create invisible economic value and stand out as a strategic group that requires rethinking marketing interaction models.

While the reasons for silence include psychosocial factors such as the desire for individual privacy, emotional caution and escape from social pressures, the interpretation of these behaviours as "ineffectiveness" by algorithmic systems leads to misleading feedback for content producers. However, it is observed that these users are intensely involved in content with sensitive themes such as parenting, health, care and personal development. Invisible loyalty also overlaps with the concept of externalities in the microeconomics literature, showing that individuals who contribute but whose contribution cannot be measured are systematically excluded from the evaluation.

Future content strategies need to build systems that focus not only on visible interaction but also on silent forms of interaction. Interface designs that are sensitive to user privacy but encourage participation should focus not only on the popularity of content but also on its information value and perception of security. At the same time, algorithms should be strengthened with inclusive learning models that take into account data such as saving, re-watching and time spent on the product page. Thus, both economic efficiency will increase and marketing strategies will be able to reach more accurate targeting.

The theoretical contribution of this study is to conceptualise silent users on digital platforms as strategic consumers of information rather than mere observers. Going beyond classical models of consumer behaviour, this approach centres on a consumer profile that avoids visibility but maximises utility. In practice, it is suggested that content producers, brands and algorithm developers develop strategies that take into account invisible user contributions. Star lists, user rankings and content filtering systems should be restructured with this new understanding; loyalty programmes should be expanded to reward invisible contributions.

Finally, this research makes a unique contribution to the literature by taking place at the intersection of microeconomics, marketing, behavioural economics and algorithm design. Further experimental, data mining-based and modelling studies to better understand silent user behaviour would be beneficial for both the efficiency of digital marketing and the inclusiveness of social content policies.

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