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Mystery of Big Data: A Study of Consumer Decision-Making Behavior on E-Commerce Websites †

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Abstract: Using big data analysis, we study the consumer life cycle based on the following four aspects: customer acquisition, participation, profit, and return visit rate. The Google Merchandise store is selected as a case study to collect data during January–December 2022. Thirteen traffic source dimension elements of the four layers were summarized and analyzed, and the following results were obtained. Consumers complete a conversion rate of 57 million. The late contact point affects the conversion rate, which is much higher than that in the early and middle periods. Reducing the number of touchpoints in the conversion increases the revenue. Understanding customers' shopping habits helps improve advertising results. Thus, website managers need to introduce Google Analytics 4 analytics at different stages for site quality and business effectiveness.

Keywords: e-commerce site; consumer behavior; Google Analytics 4

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1. Introduction

Since 1994, online stores have appeared, and after 1997, online business activities have become popular, replacing onsite stores. According to the UNCTAD report, in 2019, the scale of global e-commerce reached USD 26.7 trillion, equivalent to one-third of the global gross national product. At the beginning of 2020, eMarketer's forecast for the global e-commerce market share of retail sales was 16.1%, but with the COVID-19 pandemic, the ratio increased significantly. Since the advent of the Internet, e-commerce websites have provided a platform for buyers and merchants to transact and facilitate the smooth operation of transactions through the participation and communication of both parties. Scholars in the field of marketing and information decision-making systems believe that high satisfaction rates have a considerable impact on consumers to use or repeat purchases [1–3], which is important for influencing an individual's intention to continue using the product.

However, past literature on e-commerce platforms has focused primarily on community traits [4,5], community values [6–8], and community identity, and community loyalty [9]. There is little research on e-commerce websites and consumer decision-making behavior. Thus, we summarize, compare, and analyze the 13 traffic source dimension elements in the four major components being customer acquisition, participation, profit, and return visit rate, and we explore the connotation of the interaction mechanism of e-commerce websites.

Since the design of the purchase process affects consumer purchasing behavior [10], we used the five stages of consumer decision-making in the EKB core model [11–13] to analyze the need recognition, information search, and program evaluation (alternative evaluation) of purchasing and post-purchasing outcomes. The correlation between website service quality and the five stages of consumer decision-making behavior was considered because there were different connotations of website service quality with the consumption decision-making process. We integrated the intersection of rational views of website service quality and consumers' decision-making emotional views to develop this systematic theoretical framework.

The main objectives of this study are to (1) understand customers' shopping behaviors to improve advertising results, (2) analyze and improve the quality of the website and the business effectiveness, and (3) put forward the management implications.

The second chapter of this article reviews the relevant literature on the service quality and consumer decision-making of e-commerce websites, and the third chapter explains the analysis structure, data collection, and data analysis methods. The fourth chapter presents the research results and findings, and the fifth chapter concludes with recommendations and the direction of follow-up research.

2. Literature Review

Consumer decision-making is the process of purchasing products after considering various service quality factors [14]. The service industry attaches great importance to service process management, and service process design helps to formulate service improvement countermeasures and carry out new service development [15]. In this section, e-commerce website service quality, consumer decision-making mode, and a discussion are presented.

2.1. E-Commerce Website Quality of Service

Website service quality is related to platform quality [16–23], information quality [24–28], relationship quality [29–34], and quality of interaction [32,35]. The Internet has led to the increasing importance of e-commerce [36], and consumers can make purchases according to their needs without time or space constraints [37]. Post-purchase evaluation is an important information exchange for a two-way interaction between sellers and consumers and is also part of customer relationship management activities [38]. A high satisfaction evaluation is beneficial to website performance management, competitive advantage, repurchase behavior, and consumer trust [39], while too many bad reviews lead to low satisfaction, bad corporate image, complaints, low repurchases, negative word-of-mouth communication, and mistrust [40], so the interaction relationship directly affects consumers' willingness to repurchase [16,19,21]. Thus, we take consumer behavior as the main analysis data and then summarize the factors of website service quality that consumers value.

Understanding the connotation of website service quality and performing appropriate operations helps effectively manage customer relations. Consumers prefer a transactional website. The quality of website service is valued even beyond the product price [41], and the quality of website service is valued by e-commerce [42]. Website services are interactive such as e-learning and interaction [43,44], and application interaction designs [45] also convey messages that give customers a sense of trust in the quality of the website's services [35]. Based on the above literature review, no unified view was found to focus on the function of the network information platform. Several studies focused on the characteristics of the information provided on the transaction website, and the relationship maintenance with customers was emphasized. Thus, we explore the service quality of the website from the aspects of customer acquisition, participation, profit, and return visit rate. For consumer decision-making behavior, each component is described below.

2.1.1. Customer Acquisition

Customer acquisition is the default page after logging in and it provides detailed views without revealing personal information. Examples include customer composition (gender, age group, interests, place of residence, and device use) and browsing behavior (frequency of visits, browsing time, participation, and new and existing visitors), and customer origin/medium.

2.1.2. Participation

Participation helps understand what users have executed and what event transitions have been achieved. Websites provide preset events after announcing, and users can also set their events, which can be recorded in the participation reporting area. In addition to events and conversions, the common page views can be seen in "Participation" > "Pages and Screens", with in-depth statistics and insights.

2.1.3. Profit

Profit statements can be used to view the revenue generated by websites or their applications. Through products, advertisements, and subscription programs, these reports are used to understand the number of customer views of each selling good, the number of advertising exposure of the application, or other information on the revenue. The profit statement is divided into profit overview, e-commerce purchases, in-app purchases, and publisher advertising.

2.1.4. Return Visit Rate

The frequency and length of interaction with the website are shown after the user's first visit to the website or APP for the user to understand value according to the additional revenue generated by the user after the first visit to the website.

2.2. Consumer Decision-Making Model

Consumer decision-making patterns refer to the process of finding, purchasing, using, evaluating, and disposing of products or services [46]; participating in the acquisition, use, and disposal of products and services; engaging in decision-making processes and actual behavior [11–13]; and making decisions related to people's purchase and use of products or services [14]. It is narrowly defined as the decision made by individuals at various stages to acquire goods or services, while the broad definition includes the consumption behavior of non-profit organizations, industrial organizations, and intermediaries [11–13]. In addition, Yue and Stuart pointed out that virtual community transactions involved a range of factors with different influencing factors at different stages which affected decision-making at each stage, such as target selection, information processing, memory, degree of involvement, attitude, interference, and consumer attribution [11–13,47].

Regarding the consumption decision-making process model, several studies adopted the following three stages: pre-purchase, consumption, and post-purchase. The influencing factors include the brand, the product itself, or the type of service, while the influencing factors in the consumption stage include website services, other customers, store design, and equipment performance. These factors become the basis for satisfaction and service quality evaluation in the post-purchase stage [41]. Other studies used seven stages of consumer decision-making, including demand confirmation, information search, substitute evaluation, purchase, consumption, post-purchase evaluation, and abandonment, which were affected by electronic forums, electronic bulletin boards, and virtual community formation [48]. The previous studies divided consumer decision-making into different stages according to the time of occurrence or divided into three or five stages. The five stages of analysis included need recognition, information search, alternative evaluation, purchase, and post-purchase [11–13,47,49].

2.2.1. Demand Confirmation Stage

The demand confirmation stage is based on consumers' intrinsic demand motivation and external stimulus [11–13]. The attributes of stores affect purchase decisions, and consumers' trust level affected website performance [50]. Website performance is affected by brand identity, product knowledge, and product involvement [10], and intrinsic demand drives actual behavior. Website performance is related to the differentiation and comparison of the form of the desired need and the actual object, the experience of product use, the satisfaction value of expectations, the feeling of satisfaction, the external conditions of consumers to look for better products and designs, and international brands [48].

2.2.2. Information Search Stage

In the information search stage, third-party search service providers use intermediaries to obtain purchase information [32]. Keyword searches affect purchasing behavior and change website sales performance [51] for easy use and for consumers to trust the website more [52]. Online stores are subject to competition from external search processes [39], and they improve their profits by adjusting pricing strategies [53]. Influencing factors at this stage include knowledge [47], product presentation, evaluation of alternatives, communication, word of mouth, knowledge sharing [48], brand loyalty, and other factors, but there is a risk of information authenticity [54]. Simplifying the graphical design allows consumers to better understand whether the composition of the product meets needs such as the expected benefits, price, model, and idea guidance to obtain specific purchase objects [10]. Message response times and prices influence further information search behavior to find alternative options or go directly to the buying behavior stage.

2.2.3. Program Evaluation Stage

The scenario evaluation stage refers to alternatives to choose from [47], distinguishing alternative attributes and differences, and making it easier for buyers to make a decision. When consumers gather the required information, they evaluate various feasible solutions in four parts, as follows: evaluation criteria, beliefs, attitudes, and intentions [51]. Reference [51] pointed out that at this stage, consumers attach importance to the detailed evaluation of products on the website as well as the provision of services such as secure transaction mechanisms, money-back guarantees, and third-party guarantees. Alternatives are evaluated to select the best option by interacting with the seller [48]. If the substitution demand is met, the purchase is made, otherwise the purchase may be stopped or the search may be restarted.

2.2.4. Purchase Stage

The purchase stage refers to the best option chosen by the consumer and taking the action of purchasing [11–13] through a well-established product recommendation system and a mechanism that helps consumers identify products [55,56]. Consumers' purchasing preferences, funds, social status, and shopping preferences influence the purchase decision impact [50]. Brands can enhance the corporate image [54], and consumers increasingly rely on reviews published by social networks to guide their purchase behavior [57], influenced by purchase process design, branding, product recognition [10], product quality assurance, clear refund mechanism, and product delivery specifications. Factors such as certificates issued by trust institutions, adequate security technical descriptions, privacy protection [51], culture, and personality influence consumer purchasing behavior [48], while appropriate payment mechanisms enable consumers to increase their willingness to pay and carry out purchasing actions [58], and then enter the post-purchase behavior stage.

2.2.5. Post-Purchase Behavior Stage

In the post-purchase behavior stage, consumer perception and satisfaction have positive value, and even increase customer stickiness and strengthen competitive advantage [59]. Consumers' purchase experience and their memory influence future purchase decisions [11–13]. Good brand experience [10] provides quality returns and services [59] and brand loyalty, which increases consumers' willingness to buy and pay and recommend to other consumers [60]. Post-purchase reviews are related to satisfaction [50] and assist new consumers in making decisions [10]. Bad reviews lead to low satisfaction, poor corporate image, complaints, low repurchases, and negative word-of-mouth communication [40]. At this stage, the consumer's payment status determines whether to make a profit [20,61]. Buyers' wishful abandonment [39] or evaluation of manipulative behavior [57] are factors that contribute to disputes. Even if it is a good product, there are still cases of it being returned and exchanged. There must be a good contract as a constraint, including refund and return mechanisms, which provide consumer protection. Since consumers are dissatisfied with the goods they have chosen, leading to returns and exchanges or even litigation, mechanisms must be properly developed [59].

In summary, using the five-stage model of consumer decision-making adopted by most scholars as the research index and Google Analytics 4 (GA4), we analyze the logical concepts and influencing factors of consumers when making purchase decisions. The result provides the service quality elements of consumer demand and subsequent comparison of the transaction website at each stage.

3. Research Methods

GA4 was used as a research analysis tool to study four major reports, including customer acquisition, participation, profitability, and return visit rate. Quantitative analysis in different dimensions was carried out to specify the relationship and impact between indicators, interpret key indicators, and improve website performance.

3.1. Research and Analysis

Based on the data compilation and theoretical discussion in Chapter 2, the GA4 traffic analysis tool was applied for website traffic analysis and website performance improvement. Google Merchandise Store was selected as an analysis case, and data during January–December 2022 were collected to determine indicators and their impact on the performance of the e-commerce platform of Google Merchandise Store. Indicator traffic was analyzed and compared for websites, and feedback was gathered to improve it (Figures 1 and 2).

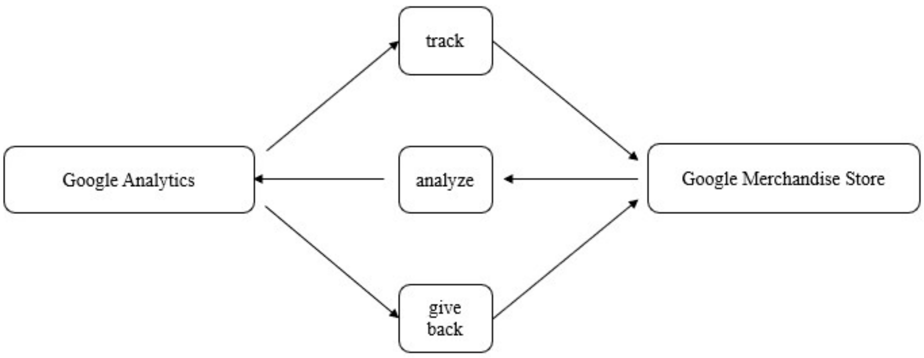

Figure 1. Research methodology.

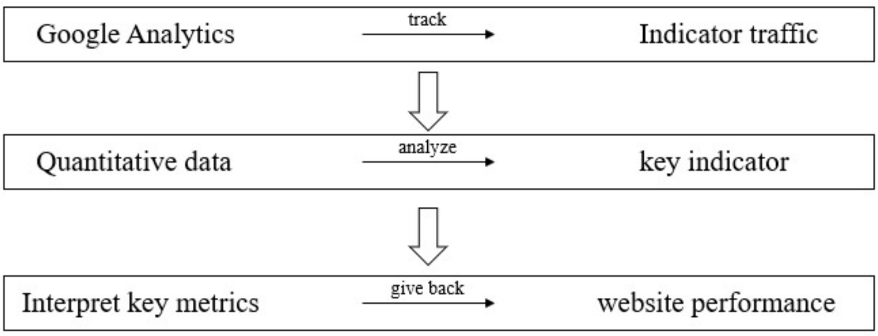

Figure 2. Analysis process.

3.2. Data Analysis

Based on the data, we interpreted the four major reports of GA4 analysis tools: customer acquisition, participation, profit, and return visit rate (Table 1). Different dimensions (Dimension) and their corresponding specific indicators (Metric) are shown in Table 2. The meaning behind the data is statistically summarized as the business significance represented by the analysis to provide a reference and suggestion for optimizing and improving website performance.

Table 1. Four major reports.

Customer acquisition	Customer acquisition is the default page after logging in to GA4, which can provide detailed viewer information without revealing personal information. Examples include customer composition (gender, age group, interests, place of residence, device use), browsing behavior (frequency of visits, browsing time, participation, new and existing visitors), and customer origin/medium (how you came to the website).
Participate	Participation allows us to understand what users have executed and what event transitions have been achieved. GA4 itself provides some preset events that can be started after announcing, and you can also set your own events, bury parameters, and then set events as transitions! Once you've set up an event or conversion, you can do more detailed drill-down tracking in the participation reporting area.In addition to events and conversions, you can also see the common page views of General GA from the past in "Participation"—"Pages and Screens", as well as in-depth statistics and insights on a page-by-page basis!
Profit	Profit reports can be used to view the revenue generated by our own websites or applications, through products, advertisements, and subscription programs. We can use these reports to understand the number of customer views of each selling good, the number of advertising impressions of the application, or other information that can bring revenue to the merchant. In the profit statement, it is divided into profit overview, e-commerce purchases, in-app purchases, and publisher advertising.
Return visit rate	Displays the frequency and length of interaction with the website after the user's first visit to the website or APP, and can be used to understand the user value according to the additional revenue generated by the user after the first visit to the website.

Table 2. Dimensions and indicators.

Dimension	**Metric**
Traffic sources, platform devices, Geolocation, Life cycle	Number of new users, interactive sessions, participation, interaction sessions per user, average participation time, event count, conversions, total revenue.

We analyzed the traffic sources, sessions, interactive sessions, participation, interactive sessions per user, activity per session, average participation time, event count, and conversions. The interaction between the dimensions and indicators was used to interpret the meaning and the impact on the performance of the website, put forward the best improvement policy, find out the best conversion path for consumers, improve the revenue of the website, and propose a guiding principle of sustainable growth. The list of specific traffic sources and indicator data collected and analyzed in this study are shown in Tables 3 and 4.

Table 3. Traffic sources.

Source of Traffic	Illustrate
Direct	Traffic from the visitor directly to the destination website URL
Organic Search	The traffic of visitors to the target website through search engines
Referral	Traffic from visitors to the target website through links from external websites
Paid Search	Traffic from visitors who enter your website by clicking on keyword ads in search results
Organic Social	Traffic from visitors to the target website via S ocial

Table 4. Indicators.

Indicators	Illustrate
User	Total number of active users
Work Phase	The number of sessions started on the website or application
Interactive session phase	Lasting more than 10 s, transitioning events, or more than 2 screen or web browsing sessions
Average time per session participation	User participation time per session
Each user interaction session	Number of interactive sessions per user (Interactive Sessions/User)
Activity per session	The average number of events per session
Participation	Percentage of interaction sessions ("interactive sessions" divided by "sessions")
Event count	The number of times the user triggered the event
conversion	The number of times a user triggered a conversion event
Total revenue	Sum of revenue from purchases, subscriptions, and advertising ("Purchase Revenue" plus "Subscription Revenue" plus "Advertising Revenue")

3.3. Research Objectives and Verification

The interrelationship between internal traffic indicators was analyzed based on the total revenue measurement. The interrelationship of sessions, interactive meeting stages, average single session participation time, interactive sessions per user, activities per session, participation, event count, and conversion was also analyzed to quantify the data, observe and explain their meaning, and find out the advantages and disadvantages. The ultimate goal is to improve the physical fitness of the site and enhance the performance of the website (Figure 3).

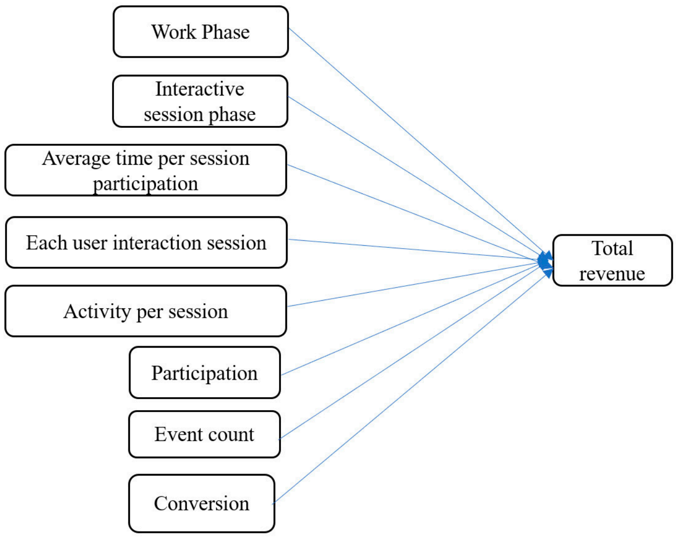

Figure 3. Relationship between internal traffic indicators.

The impact of traffic sources was investigated on total website revenue, as well as the impact of sessions, interactive sessions, average time per session participation, interactive sessions per user, activity per session, participation, event count, and conversions as mediating factors on total revenue (Figure 4).

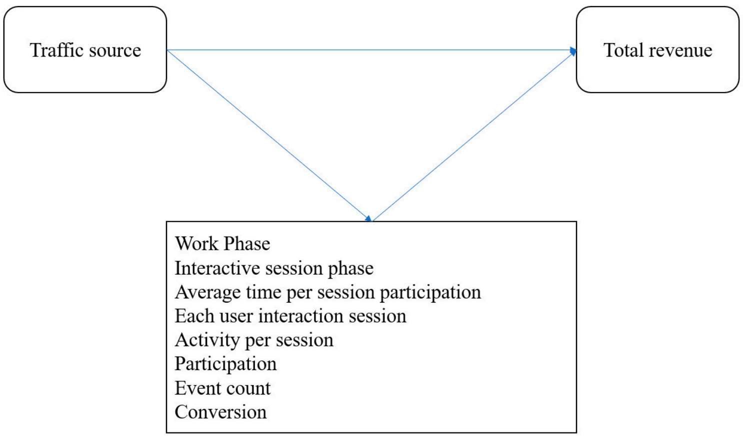

Figure 4. Relationship between traffic sources, indicators, and total revenue.

4. Empirical Analysis

Target websites were investigated based on GA4. The data of 365 days were collected and used for quantitative statistical analysis. The relationship between different dimensions, specific indicators, and the impact on website performance was analyzed to determine website performance indicators. The traffic sources of Google Merchandise Store were quantified and analyzed. The results are presented in Tables 5 and 6. The correlation and impact between external traffic and indicators are discussed later in this article.

Table 5. Basic traffic data of target website.

During the analysis	1 January 2022~31 December 2022
Total number of days	365 days
Site name	Google Merchandise Store
Site type	E-commerce
User (Person)	896,921
New User (Person)	843,322
Participation (%)	63.34
Average time involved	1 min 22 s

Table 6. External traffic data of target website.

During the analysis	1 January 2022~31 December 2022
Total number of days	365 days
Site name	Google Merchandise Store
Site type	E-commerce
The type of traffic from the external source	Flow rate (times)
Total external source traffic	896,921
Direct	336,892
Organic Search	312,536
Unassigned	74,139
Referral	49,625
Paid Search	47,906
Display	44,783
Paid Shopping	19,655
Organic Social	9615
Paid Video	9586
Email	9220
Organic Video	7451
Affiliates	2426
Organic Shopping	1889

4.1. Website Indicator Performance

The traffic metrics of the target website were analyzed with SPSS to find the degree of mutual influence between the indicators (Table 7). The result shows that the meeting stage is positively correlated with the total return. The result of the indicator corresponding to the traffic source is shown in Table 8. There is a positive correlation between interactive work stages and total returns.

Table 7. Sessions and total revenue.

		Total Revenue
Work Phase	Pearson correlation	0.981 **
	Saliency (two-tailed)	0.000
	N	13

** Correlation is significant at the 0.01 level (double-tailed).

Table 8. Relationship between interactive sessions and total revenue.

		Total Revenue
Interactive session phase	Pearson correlation	0.976 **
	Saliency (two-tailed)	0.000
	N	13

** Correlation is significant at the 0.01 level (double-tailed).

The relationship between the participation time in the average single work stage and the traffic source is shown in Table 9. There is no correlation of the participation time in the average single work stage and the traffic source.

Table 9. Average participation time and total benefit per work phase.

		Total Revenue
Average time per session participation	Pearson correlation	0.240
	Saliency (two-tailed)	0.431
	N	13

Each user's interaction stage does not correlate with total revenue (Table 10).

Table 10. Interactive sessions and total revenue per user.

		Total Revenue
Each user interaction session	Pearson correlation	0.172
	Saliency (two-tailed)	0.573
	N	13

The activities at each work stage are not correlated with total returns (Table 11).

Table 11. Activity and total revenue per session.

		Total Revenue
Activity per session	Pearson correlation	0.233
	Saliency (two-tailed)	0.444
	N	13

There is no correlation between participation and total revenue (Table 12).

Table 12. Participation and total revenue.

		Total Revenue
participation	Pearson correlation	0.151
	Saliency (two-tailed)	0.621
	N	13

The event count is positively correlated with the total revenue (Table 13).

Table 13. Event count and total revenue.

		Total Revenue
Event count	Pearson correlation	0.987 **
	Saliency (two-tailed)	0.000
	N	13

** Correlation is significant at the 0.01 level (double-tailed).

Conversions and total revenues are positively correlated (Table 14).

Table 14. Conversions and total revenues.

		Total Revenue
Conversion	Pearson correlation	0.970 **
	Saliency (two-tailed)	0.000
	N	13

** Correlation is significant at the 0.01 level (double-tailed).

4.2. Comparison of Website Traffic Source

The analysis and comparison process are shown in Figure 5.

The impact of traffic sources was analyzed on total website revenue, the impact of sessions, interactive sessions, average time per session participation, interaction sessions per user, activity per session, participation, event count, and conversions. The analysis results are shown in Table 15.

The standardized coefficient of traffic source and total revenue was β: 0.979 **** at the significance level of 0.000, showing that traffic source is positively correlated with total revenue. Thus, traffic sources affected total revenue. Interactive sessions are negatively correlated with total revenue as an intermediary factor between traffic sources and total revenue (β: −1.998 ** at the significance level of 0.008). The average participation time of a single work stage is positively correlated with the total revenue as an intermediary factor between the traffic source and total revenue (β: 0.234 * at the significance level of 0.043). Each user's interaction session does not correlate with the total revenue as the intermediary factor between the traffic source and the total revenue (β: 0.150 at the significance level of 0.103). Activity at each work stage is negatively correlated with total revenue as an intermediary factor between traffic sources and total revenue (β: −0 419 * at the significance level of 0.033). Participation is positively correlated with total revenue as an intermediary factor between the traffic source and total revenue (β: 0.155* at the significance level of 0.040). The event count is positively correlated with the total revenue as an intermediary factor between the traffic source and total revenue (β: 2.739 ** at the significance level of 0.010). Conversion does not correlate with total revenue as an intermediary factor between the traffic source and total revenue (β: −0.683 ** at the significance level of 0.399).

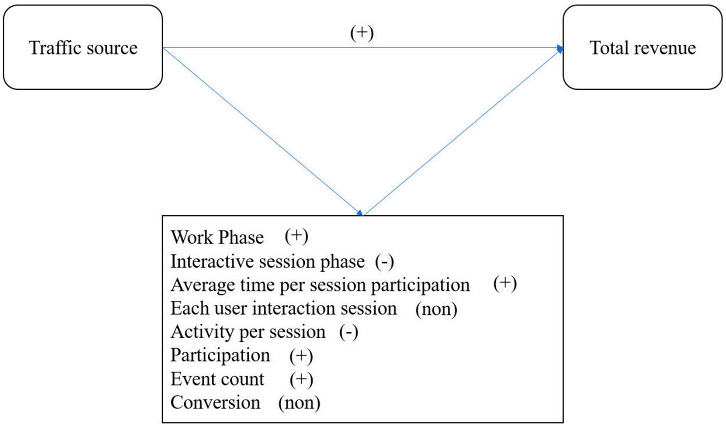

Figure 5. Website traffic source analysis and comparison process.

Table 15. Regression coefficient analysis.

Coefficient a						
Model		**Non-Normalized Coefficients**		**Normalization Factor**	**T**	**Salience**
		B	**Standard Error**	**B**		
1	(constant)	−21,056.449	26,123.721		−0.806	0.437
	Traffic sources	3.005	0.190	0.979	15.802	0.000
2	(constant)	−121,831.188	81,298.402		−1.499	0.208
	Traffic sources	2.822	2.388	0.919	1.182	0.303
	Interactive session phase	−6.074	1.220	−1.998	−4.978	0.008
	Average time per session participation	1931.629	662.366	0.234	2.916	0.043
	Each user interaction session	113,799.812	54,065.559	0.150	2.105	0.103
	Activity per session	−15,285.154	4758.270	−0.419	−3.212	0.033
	Participation	296,519.318	98,753.591	0.155	3.003	0.040
	Event count	0.224	0.048	2.739	4.672	0.010
	conversion	−1.328	1.409	−0.683	−0.942	0.399

The analysis result of the traffic source data of the Google Merchandise Store is shown in Table 16. The number of days required for conversion was 0 with 577,899.00 conversions accounting for 37.85%. For Organic Search, after 1 touchpoint, the number of days required to convert was 0.9, and there were 327,165.00 conversions accounting for 21.43%. Paid Search, after 1 touchpoint, showed the number of days required to convert was 0.9 with 71,781.00 conversions accounting for 4.70%. The results showed that Direct, Organic Search, and Paid Search resulted in higher conversion times, shorter changeover time, shorter path length (all contact points), and higher transition.

Table 16. Conversion path.

	Traffic Sources	Conversion	Purchase Proceeds	The Number of Days It Takes for the Conversion to Occur	The Contact Point That Passed before Conversion
		1,526,776	2,572,828.91	1.69	2.78
1	DirectDirect	577,899	1,155,992.7	0	1
2	Organic Search	327,165	81,713.78	0.9	1
3	Paid SearchPaid Search	71,781	26,162.68	0.9	1
4	DisplayDisplay	50,836	161	0.57	1
5	UnassignedUnassigned	45,037	909.44	0.01	1
6	ReferralReferral	41,841	38,973.62	1.27	1
7	Organic Search × 3	38,230	112,658.25	4.67	3
8	Organic Search × 4	32,637	85,832.99	3.54	4
9	Paid Shopping	27,260	11,338.76	0.89	1
10	Organic Search × 2	23,040	126,939.31	4.11	2

5. Conclusions and Recommendations

The purpose of this study is to analyze the traffic data of the Google Merchandise Store with GA4 and explore the relationship between the variables of related traffic indicators. The impact of website performance was also investigated. The results were used to make website operation suggestions, improve website content, optimize website physique, enhance website performance, and achieve the purpose of long-term development of websites. The conclusions of this study are described as follows.

The results of this study show that the correlation between the work stage and the total income is significant. Thus, the working stage is positively correlated with the total return, and the total income is subject to the related variables. The interaction session is significantly correlated with the total revenue, indicating that the total return is affected by the change in the interactive work stage variables. The participation time in the average single work stage is not significantly related to the total return. The correlation between each user's interactive session and total revenue is not significant. The activity of each work stage is not significantly related to the total return. The correlation between participation and total revenue is not significant, while the correlation between event count and total revenue is significant. Event count is positively correlated with total revenue, and the conversion is also significantly correlated with the total return.

The traffic sources are positively correlated with total revenue, and traffic sources affect total revenue, while interactive sessions are negatively correlated with total revenue. When interactive sessions increase, total revenue decreases. The average participation time of a single work stage is positively correlated with the total revenue. Each user's interaction work stage is not related to the total revenue. The activities of each work stage are negatively correlated with the total revenue. Participation is positively correlated with total revenue, and event count is positively correlated with total revenue. Conversion does not correlate with total revenue.

The results of this study can be used as a reference for website managers or digital marketers to find the best conversion path model for the target website at various specific comparison times.

Practical suggestions can be made for website operators engaged in online store operation or shopping websites.

First, the interaction work and the activity of each session needs to be reduced to increase the average time per session, participation, and event count, which can help increase total website revenue. Second, the number of days for a conversion needs to be reduced so that a conversion can increase conversion rates. Website managers or digital marketers must find the best conversion path model for the target website at various specific comparison times. The traffic source is an important variable affecting conversion. Direct, Organic Search, and Paid Search have high conversion rates. The demand identification stage, information search stage, and solution evaluation stage must be designed to meet consumer's needs and to motivate purchasing.

As technology is changing rapidly and information in the online world is updated rapidly, future follow-up research is required. First, it is necessary to collect and analyze data from different dimensions and metrics. We only analyzed the two dimensions of visitor type and traffic source to discuss specific indicators such as bounce rate, page view rate, departure rate, click-through rate, and conversion rate. Other dimensions and indicators need to be analyzed to increase the integrity of the theoretical framework. Other analysis methods need to be adopted with GA4 traffic analysis tools to analyze the relationship between various dimensions and indicators more accurately and propose more reliable and powerful analysis results. Then, the research analysis method is more evolved and strengthened, which is worth exploring for subsequent researchers. The main source of visitors to the Google Merchandise Store, the target website of this study, is the United States. In the future, other variables that affect different cultural backgrounds under different cultural differences also must be explored.

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