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Table of contents

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How Reliable Is Google And Facebook Mobility Data?

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Abstract In the wake of the COVID-19 pandemic, scientists were eager to access mobility data to model the virus's spread. As human mobility and interaction play pivotal roles in virus transmission, data from tech companies, derived from mobile phone usage was hastily adopted. However, evidence suggests that these datasets lacked sufficient reliability, underscoring the importance for scientific research to exercise caution with new datasets lacking well-documented methodologies and transparent metadata..

Keywords traffic counting, traffic measurement, transport statistics

JEL L91, R41

1. Introduction

During the COVID-19 pandemic, there was a need for near-live tracking of mobility data. However, neither the public transport authorities nor the transport service providers typically had such data, and there were no aggregated databases for transport as a whole. It was therefore very helpful that technology companies published data with daily changes. During the epidemic, however, there was naturally no time to examine the reliability of this almost live data. In this paper we want to examine what we can learn about the accuracy of big tech databases. First, however, it is worth reviewing what other measurements are available tacking transport and mobility.

Mobility data can be used for several purposes, including transport planning and operation, urban and regional developments, corporate fleet optimization. Even though vehicles and travelers are equipped with digital devices for a longer time, e.g. smartphones and GPS trackers, publicly available data for transport and mobility are based mainly on in-person counting and automatic counters of embarking and disembarking passengers of public transport vehicles and/or stations. The data is collected mainly by statistics offices, based on information provided by public transport operators (PTOs) or public transport authorities (PTAs) operating trains, trams, busses, metros, and traffic counting by infrastructure managers. However, these data collections are not internationally standardized, and the validation and control of data is an ever greater challenge [1]. Digital ticketing has made it possible to collect information much faster and more precisely [2]. Data collection is considered accurate, the background and limitations of the collected data are well understood by professionals working with it. However, the major limitation is the very time-consuming publication. Most datasets available for international comparison are annual and published several months after the end of the year. Data publication of the different PTOs differs in format, availability and therefore it is complicated to analyze recent trends in the international context, it would involve a lot of manual data collection. Especially in a pandemic situation that is not viable, even monthly data releases are far from the ideal.

There are novel ways to collect and publish traffic information by statistics offices. In Hungary, for instance the National Statistics Office uses the monthly toll information of heavy goods vehicles, which pay road usage fees based on the distance driven. Cameras and automatic measuring points data are used to calculate passenger car traffic [3]. Similar data collections are increasingly advancing in many countries, such as Germany [4].

Ridership counting technologies have become automated and digitalized in recent decades. Previously, occasional counting was the most common method of accounting the ridership of public transport vehicles. For closed systems, where passengers have to enter through gates, (e.g. metro systems), boarding could be measured well, but this gave no information about where people were traveling to. The introduction of automated fare collection systems has helped to improve data quality [5]. On busses, trams, trolleybuses mass based counting were introduced – the air ride suspension system could monitor and calculate the load of passengers, and from the counted mass, the number of passengers could be calculated [6]. Automated passenger counters of vehicles nowadays use infrared beam methods for detection. Since the 2010s, these systems have been widely used, especially in Europe and the United States, but „such systems are expensive and inaccurate for scenarios such as multiple-passenger boarding and alighting” [7]. Tests conducted by Kotz et al. (2016) concluded, that air suspension-based measurement has a −2.4% error, while infrared beam had a 17.5% error. Other studies report lower accuracy for mass-based counting: the machine learning algorithms had 91% accuracy, but the trained algorithms were 61% accurate in recording boarding events [8]. Automated passenger counting is limited to a fraction of the fleet of PTOs, due to the high cost of the implementation, therefore estimations are used to model total ridership [9]. This further limits the accuracy of the ridership data.

Technology helped speed up the ridership counting processes and improve data quality. In Santiago, Chile, based on mobile phone location data, the transit mode of individuals by mode of transport (mass-transit, motorized, active modes, and taxi) could be separated [10]. Geospatial data analysis for ridership and modes of transport is rapidly improving, and the accuracy and results are convincing [11]. Based on the acceleration, geospatial position, and proximity of the transport network, the mode of transport and ridership information can be precisely analyzed. Not only can actual ridership data be measured, but predictions are becoming ever more precise [12]. In Sanghai, China, a novel model was introduced to analyze urban activity dynamics. Multiday, 24–7 activity chains of mobile phone data were fuzed with travel surveys, resulting in a robust model to calculate ridership and mode of transport data [13]. CCTV footage could also be used to measure social distance rules measurement [14]. Estimating bus ridership was also solved based on Wi-Fi probe requests at stops [15].

Several novel and faster data sources for tracking transport were introduced after the COVID-19 pandemic. Although the methodology varies country-by-country, there are no internationally comparable datasets. During the pandemic, there were no daily, weekly, or even monthly continuously updated datasets for tracking mobility, and scientists and decision-makers were eager to find possibilities to track the results of governmental restrictions on mobility. The Oxford Coronavirus Government Response Tracker (OxCGRT) project calculated a stringency index of government measures, but it could not show the real effect on mobility and how it influenced the number of interactions between people [16].

Tech companies use location and behavior data since a longer time for ad-targeting and data mining purposes and provided mobility information while the COVID-19 pandemic for free for the public [17]. Alphabet Inc. and Meta Platform Inc. have published their dataset since the beginning of 2020. These were published under the names of their flagship services Google and Facebook. Data access to information collected by these tech companies was very limited for scientific purposes, but access for authorities, especially for countries outside the United States it is still hardly possible. These corporations hold vast amounts of data that could be useful for governments in the case of natural disasters, epidemics, or even tracking policy impacts. Due to the lack of clarity regarding the storage and utilization of data, both national and international regulations regarding data access and usage remain ambiguous. Consequently, only data that has been made publicly accessible by technology companies can be used [18].

These reports rapidly gained momentum in 2020 and were not only used by mass media, but scientific research and international organizations also started to use them [19]. Although these mobility datasets have been used for a very wide range of analyses and research, hardly anyone seems to question the reliability and background of these datasets. One would expect that in the case of a new dataset, there is a need for high data quality and reliability before any scientific conclusions can be drawn. Questions have been raised about the representativeness of the Facebook and Google mobility data [20]. Previous research on mobile phone location data usage for human mobility indicators in Shenzen, China, suggested that "researchers should carefully interpret results derived from this type of sparse data in the era of big data" [21]. In the case of Facebook data for the United Kingdom, it was shown that the users are representative of the population [22]. Other research pointed out, that compared to the European population Facebook's users are overrepresented in the 20–40-year-old, above-average income level, higher level of education user groups [23]. The representativeness of social media data in urban areas in Spain was also discussed, concluding that it may not be entirely representative [24]. A previous study in the United Kingdom concluded that "social media data cannot be used to generalize to any population other than themselves" [25]. Regarding mobility data used in the COVID-19 pandemic, a meta-analysis of prior research concluded, that passive data collection modes (e.g. mobile phones and wireless networks) tend to have higher representatives due to higher penetration ratios [26]. A study comparing Apple, Google, Twitter, and Descarte Labs mobility data argues that the representativeness of each data source largely depends on the demographics of users of these services compared to the demographics of the population of a country, region [27]. They also recognized the inconsistencies of these mobility datasets. Despite the open question regarding the representativeness, whilst the pandemic, any rapidly available information was very useful. Not only was the prompt publication of these datasets crucial, but they also provided standardized information for most countries worldwide. Data provided by tech companies is especially crucial in those countries and regions, where traditional data sources on mobility are scarce, such as in Africa [28].

Not only Google and Facebook provided mobility information, but also Apple. The Mobility Trends Report is not only not updated anymore, but it was also removed from the companies' website in April 2022 [29]. As the data could not be accessed anymore, it had to be excluded from this analysis. This example also shows how unreliable Big Tech provided information is. Some datasets were not global, Foursquare Community Mobility Reports was only available for the United States [30]. Researchers have also used Twitter data to model mobility patterns, but penetration rate is really low in most of the countries [31].

In this article firstly the impact of tech companies' mobility reports on scientific analysis will be assessed. Following this, the methodology of these data collection methods is presented. The reliability and validity of mobility reports will be analyzed in different ways, e.g., by measuring the different

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sources in relation to each other and to official data sources. Based on the analysis, conclusions will be drawn.

2. Impact of mobility data on scientific research

It is unprecedented how quickly mobility datasets have become part of scientific research. After weeks of the first dataset releases, pre-print articles appeared online mainly focusing on the correlation between mobility changes and the spread of COVID-19 virus. Table 1. shows the number of scientific articles by database in which tech companies' mobility reports were used. Healthcare- and pandemic care-related journals, which are part of the PubMed database, have exhibited less interest in the use of these datasets than other research fields.

Table 1. Scientific articles using Google and Facebook mobility data

Keyword	Google Scholar	Science Direct	PubMed
Facebook Data For Good	542	44	9
Google Community Mobility Reports	973	160	31
Facebook mobility	231	14	0
Google mobility	4260	424	92

There were already systematic literature reviews conducted on the relationship between mobility and the COVID-19 pandemic. A review article from 2021 featured 14 articles, all of which were based on Google Mobility Data, but without mentioning possible data validity and reliability issues [32]. Another review paper also from 2021 concluded that the overwhelming majority of research papers on COVID-19 and mobility were based on Google Mobility data [26]. In China research also focused on the technology enabled datasets, but not only the global Big Tech players, but they used mostly the local Baidu and Tencent provided mobility datasets [33].

Lee and Eom (2023) analyzed hundreds of research papers on this topic. Their gigantic work shows that research in this field was conducted in two main categories: (1) mobility changes measured by transport volume and (2) survey-based studies to investigate changes in personal travel behavior. In the first case, most of the studies were either based on Google, Facebook, and Apple provided mobility data, or they were part of the analysis. Also a common feature is that most studies not relaying on tech company provided datasets analyzed a certain transport mode; therefore, mobility as a whole could not be measured.

Despite considerable interest from researchers and governments in the use of tech companies' mobility data, all of these previously provided datasets have been discontinued. Further research cannot evaluate their reliability and usability in normal, non-pandemic situations. However, mobile phone-based mobility data are also collectable without these companies. Analysis of 3.8 million smartphone trajectories revealed that just one data source per 10,000 people could generate mobility data of comparable quality to that provided by Big Tech during the COVID-19 pandemic [35].

Studies using Google and Facebook provided mobility data compared the compliance of social distancing rules between countries [36], measured greenspace access [37], modeled the impact of mobility restrictions on infectious disease transmission [38]. Researchers also used these datasets to model modal shares in passenger transport [39], predicted tourism demand [40], analyzed the relationship of mobility and crime [41], and modeled residential waste generation behavior [42]. Numerous studies analyzed social aspects, but there were not that many that used these datasets to actually predict and model the spread of the COVID-19 virus. Numerous models were created to model the spread of the virus based on mobility reports [43], [44], [45], [46]. The ex-post validation of these models was a much less frequently researched topic. However, a study found evidence, that reported mobility was correlated with the seasonality of COVID-19 in the Netherlands [47] .

ports were used. Healthcare- and pandemic care-related journals,

3. Methodology of mobility data by Google and Facebook

The greatest advantage of mobility datasets provided by Big Tech was the very easy accessibility for virtually all countries of the world. This is highly advantageous because even datasets of global international organizations can collect only very basic statistics for all countries. Therefore, having access to similar data globally was a very useful novelty.

However, there were major differences also compared to international statistics. Statistics offices, international organizations not only publish data, but also share metadata information. This includes information about the meaning of data, which statistical methods were used in the production of it, and how the data can be accessed, etc. Metadata modeling has a long tradition in official statistics [48]. Software and digital data are increasingly shared rapidly, and people contribute to online developments. The most popular social coding platform is GitHub, where the documentation of software coding and used data is described [49]. This shows, that there is a model for documenting tech provided data too.

The mobility databases of Google and Facebook provided very limited information on data collection, validation and data background up to the standard of metadata, or GitHub style documentation. Facebook mobility data is called Facebook Data For Good Data Range Maps, and data is based on comparing mobility of every single day to the average mobility of February 2020. The database was published until May 22. 2022, and no update is available after that date. The data includes information on movement, but it is not collected by which means of transport.

The only information on what is exactly provided is a .txt file with 132 words called “How to understand this data”.

This cannot provide any detailed information on what is actually in the dataset [50].

The database is provided in the U.S. for each county, for the European Union for NUTS-3 level and for level 2 divisions from the Database of Global Administrative Areas (GADM) for other countries. The mobility is understood if people leave or not leave a c. 600 x 600 meters zone, which is part of Bing mapping system and is coded as level 16.

Google Community Mobility Reports were available from February 15, 2020, till October 15, 2022. The baseline is the median value for the corresponding day of the week, during the 5-week period between January 3. 2020 and February 6. 2020. Every single day in the dataset is measured to the average of this period. High level categories are used to track the time spent by users. Google did not publish in detail how they measured this, only two examples are presented on the website [51]. The 'Understand this data' section is 681 words long. There is a description available on the anonymization process. It states, that data of users were used that voluntarily opted in for location tracking, which is turned off by default (Akhmet, et al., 2020).

The dataset contains comparisons for time spent in six categories (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, residential). Transit is referred to by numerous paper as an equivalent of public transport, but it includes, for instance taxis stations, car rental companies, highway rest stops). There is no detailed explanation, metadata available. From the examples provided, it seems Google calculates time spent within different locations, but does not calculate with time spent in transit. Both datasets provide daily changes in mobility at different geographical levels. As Google and Facebook did not share the baseline values, it is also hard to know how realistic the datasets are for the time spent by people.

4. Limitations of data collected by Google and Facebook

4.1. Lack of information on sample sizes

Both Google and Facebook share very little information about the methodology of data collection. A major problem is that we know nothing about sample sizes and their representativeness, the differences in these in the regions and countries. It is not known whether the number and composition of the sample may vary from day to day or not. A very high proportion of people use mobile devices and the services of Google and Facebook, but their penetration rate is very different by region. Furthermore, not all users of these services automatically provided data for the datasets. As described by Facebook in a blog post, "only people who opt in to Location History and background location collection are included. People with very few location pings in a day are not informative for these trends, and, therefore, we include only those people whose location is observed for a meaningful period of the day" [53]. This is crucial information, as we cannot know the proportion of people sharing their location history, and most importantly how people sharing their location are representative of age, education, income, etc. Different data protection regulations by countries could also impact what information is available and how punctual and/or representative these are on mobility. All of these aspects can change over time, which also has a direct impact on data quality.

In the case of Google, our knowledge is further limited. Google states, "Insights in these reports were created with aggregated, anonymized sets of data from users who had turned on the Location History setting, which is off by default. People who have Location History turned on can choose to turn it off at any time from their Google Account and can always delete Location History data directly from their Timeline" [54]. This description suggests that only a fraction of users authorize data collection. While this alone would not be problematic if the dataset were representative or randomized, the challenge lies in the uncertainty about whether 1%, 10%, or 90% of the population provides mobility data to tech companies. Furthermore, we lack information on how these figures vary from country to country or over time, and whether any adjustments are made to account for such changes.

4.2. Missing information on sociodemographic characteristics

Not only are sample sizes not known, but basic sociodemographic data were also not published. Therefore, it cannot be determined whether or not the dataset is representative for the given country, region or city. It can realistically be assumed that as younger people tend to use their smartphones more actively, the penetration of Big Tech services is higher in younger age groups and lower in older age groups. Research shows that smartphone and social media usage varies by age, employment status and education a lot [55]. As mobility patterns differ by age, mobility data provided by Big Tech should be less representative of society as a whole. In contrast, as demonstrated in the Introduction, several studies have been able to establish the representativeness of Google and Facebook users concerning the populations of different countries. However, they focused on total users, and information on users who authorize the tracking of location history is not available.

4.3. Different concepts of measuring mobility

Both reports provide insights into mobility, but both understand it very differently. Google measured the time spent at locations that they think are connected to transit. This is highly questionable, especially during the pandemic. If people spend more time at a bus stop, it does not indicate that they travel more, especially as under the mobility restrictions due to COVID-19 the interval of public transport services grew considerably. In contrast, car travel became faster as there were fewer traffic jams. Big Tech mobility data is not split by mode of transport, so we cannot determine the proportion of leisure (e.g. people went for a walk) and transport related (went for baking for sport, or to the office to work).

The change in modal share alone had a high impact on the time spent traveling, and the pandemic had a very substantial effect on this [56].

Facebook also did not differentiate by type of mobility: they measured how often people left an approximately 600 meter by 600 meter Bing tile. This methodology has a considerable drawback: people at the center and at the border of polygons are measured differently. The setup of the grid system has a direct impact on mobility in different cities. Also, population density will determine the outcome for Facebook's mobility measurement a lot – as in high-density urban areas, the same movement by this measure can result in much more social interactions, than in low-density suburban areas.

None of the data providers addressed the issue of tracking people vs. tracking devices vs. users. Nowadays, it is common for people to log in onto several devices at the same time, e.g. onto a smartphone, a tablet, or a laptop. Users can also create multiple user data for their devices, for instance, for their smart TV. These patterns are very different in high-income and low-income countries, which has to have a very substantial impact on data quality, but no information is accessible on how they treated these issues. We cannot know, for instance, whether the provided data is an aggregate, filtered information on users, only mobile devices were taken into account, and how they treat multiple logins.

Transit data measured by Google seems to miss transit time; it only measures time spent without movement in transport-related locations. For instance, the time spent at a gas station is measured, but not the time traveling by car. Travel by public transport is tracked only by the time spent in a station. In the case of a railway station, it seems impossible to differentiate between the time spent waiting for trains and/or time spent shopping. In addition, the time spent walking and cycling is challenging to split between transit and time spent in parks. Lockdowns under COVID-19 created a higher demand for biking and walking, which would make the understanding of differentiation important [57].

Very limited information is available about the mobility datasets provided by Google and Facebook, but many inextricable issues arise regarding them. It is highly doubtful that these datasets could precisely illustrate the real mobility and transport changes in societies, because:

- No information is available on the sociodemographic characteristics of data providers and whether they are representative for counties and cities or not.
- The understanding of mobility and transport is not well defined.
- Datasets are based on time spent, whereas transport measurement is generally based on the number of trips and distance traveled by passengers.
- No information is available if data are based on devices or users.
- Data are not available for non-pandemic periods to check validity under normal conditions.

5. Results

Three data analyses were selected to assess the reliability of Google and Facebook mobility data. First, the relationship between these datasets was analyzed. Second, they were compared with the measured public transport ridership in three European cities. Third, the total transport volumes of Hungary were compared with tech company provided mobility data.

5.1. Relationship between Google and Facebook mobility data

Tech companies provided similar mobility data, but in a very different data structure, and their methodology was also different. The easiest way to check their reliability could be to compare the datasets. Therefore, the hypothesis is that if the data provided by Google and Facebook do not correlate with each other, then one of them is less representative of mobility.

Although it sounds like a trivial task, the two databases cannot be easily compared. Google and Facebook used different geographical territories. Country, sub-regional, and city levels are available. However, the geographical breakdown is different country-by-country; therefore, regions and cities with insufficient data were excluded from the publication. The exclusion happens on a daily level, so sometimes just 1-2 days are missing from the dataset, and on other occasions there was only data for only a few days.

To compare both datasets, the most detailed city level was chosen. For that, 320 cities could be identified in both datasets, for which data were available for at least 92% of the days (e.g. more than 750 days) in the period from March 1, 2020 to May 22, 2022 (813 days), a total of 259.830 observations could be analyzed (Table 2).

Table 2. Descriptive statistics of Google and Facebook data analyzed

Keyword	Google Scholar	Science Direct	PubMed
Facebook Data For Good	542	44	9
Google Community Mobility Reports	973	160	31
Facebook mobility	231	14	0
Google mobility	4260	424	92

The average of the changes for these cities showed that Google registered a higher decrease in mobility in 2020 and the first half of 2021 (Figure 1). In the second half of 2021, both data sources showed similar changes, but in 2022, Google showed a bigger rise in mobility than Facebook.

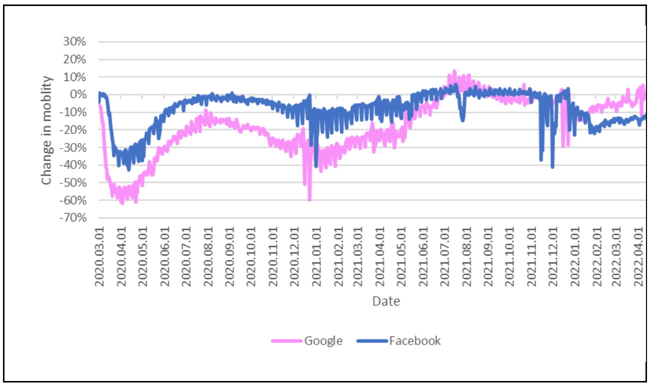

Figure 1. 1 Change in mobility in regions available in Google and Facebook database (average of regions, n=320).

The correlation between Google and Facebook mobility change indicators was 0.35, therefore it is considered very weak (p-value < 0.001). Measuring correlation only between the two variables could lead to false results due to the Simpson's paradox. As the datasets include several groups, it could happen that the trend of these groups, which are 320 regions, disappears or even reverses. To overcome this phenomenon, the multilevel correlation was calculated. This shows a slightly higher correlation of 0.38, which is still weak (p-value < 0.001) (Table 3).

Table 3. Descriptive statistics of Google and Facebook data analyzed

	Correlation coefficient (R^2)	P-value	Observations (n)	Number of groups
Correlation	0.35	< .001	259830	-
Correlation (multilevel on regions)	0.38	< .001	259830	320

By visualizing the mobility changes in Google and Facebook databases, and highlighting the correlation between those on the city level, it can be seen that the correlation is very different region by region (Figure 2).

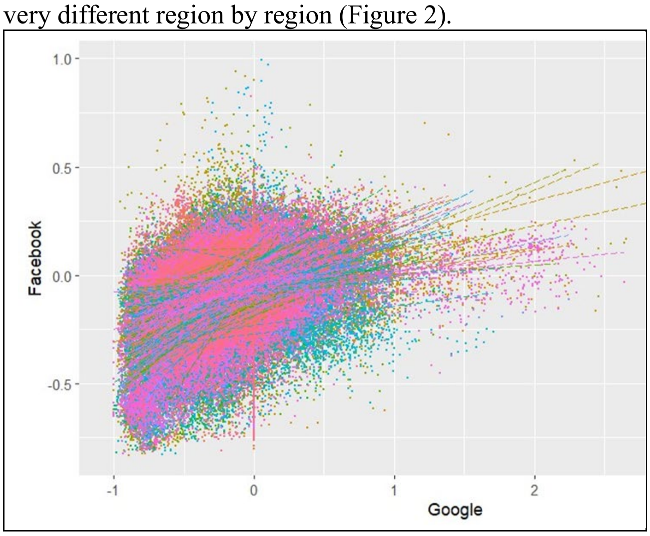

Figure 2. Mobility changes registered by data by Google and Facebook by regions (points) and correlation (lines).

At the country level, the correlation is also very different from country to country. This was measured for the same period as the region-level comparison. In some countries, the correlation is significant, but in the case of Cabo Verde, it is negative and insignificant (Figure 3). The results suggest, that either one of the datasets or both are unreliable for representing real mobility changes at the regional level of the 320 analyzed regions.

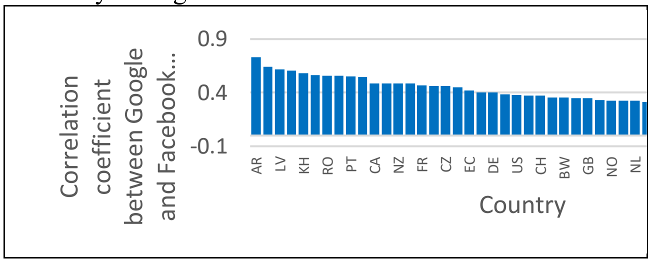

Figure 3. Average correlation between changes in Google and Facebook mobility data by country

5.2. Mobility data and public transport data

Public transport and road traffic measurements in cities are available nowadays, even with practically live data. Fifteen European Union major cities have been asked to share daily detailed information about public transport ridership. Five of them replied, and three could provide data. The public transport company of Berlin, Germany (BVG) has data, but it is not sharing it. Vienna, Austria has no data collection, passenger numbers are estimated on a yearly basis only. Budapest, Hungary and Warsaw, Poland shared weekly datasets, Stockholm, Sweden monthly. The methodology is also different: in Budapest, data are available only from bus lines and some tram lines (c. 40% of total passengerkm of the urban transport), whereas for Warsaw and Stockholm, all transport modes are included. Budapest and Warsaw provided the daily traffic change compared to the baseline in percentage, and Stockholm provided the boarding and passengerkm values.

In the case of Budapest, data are published on a weekly basis based on the automatic infrared counting system of busses and trams. The baseline of the change is the average traffic measured on school days in 2019.

In Stockholm, the Automatic Passenger Count (APC) equipment registers every boarding by all types of urban transport operated by the Greater Stockholm Local Transit Company (SL). Values for boarding and passengerkm were provided. The total value for all trips includes the calculated values for trips without APC vehicles (e.g. due to technical failure). The change in the number of passengers was calculated to the 2019 average as the baseline, similar to the other two cities. The monthly values were converted to weekly by evenly distributing the daily average per day.

In Warsaw, most busses (88%) are equipped with an infrared automatic counting system. The metro system is closed with barriers, therefore every trip is registered. The weekly change in passenger numbers is calculated as the comparison to the average of the period February 24, 2020 to March 8, 2022.

The daily mobility changes available in the Google and Facebook mobility datasets were taken as a weekly average. Due to different bases by city and data source, other periods

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were used for comparison, and all changes were compared to the 10th week of 2020 (Figure 4).

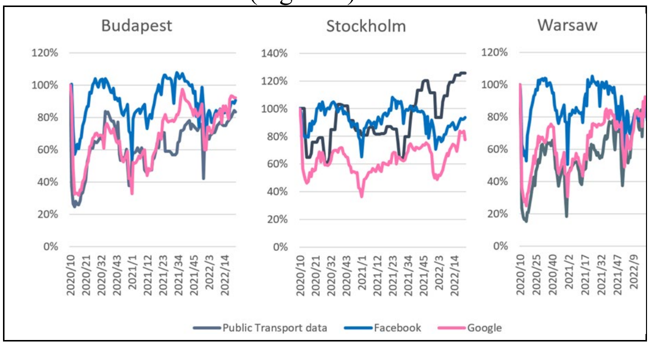

Figure 4. Comparison of weekly public transport passenger number changes in Budapest, Stockholm and Warsaw registered by public transport operators and Google and Facebook mobility data (week 10 of 2020=100%)

5.3. Total transport demand compared to Google and Facebook in Hungary

The Hungarian Central Statistics Office publishes quarterly detailed data for urban and suburban public transport as passengerkm and monthly changes in domestic passenger car transport on national roads. The Eurostat annual vehiclekm for national passenger car transport is also available. Vehiclekm can be translated to passengerkm with a calculation of 1.2 passengers per car, which is used in transport counting in Hungary [58]. From these the quarterly average change for the most important passenger transport modes could be aggregated, including intercity bus services (bus, rail, but even airplane and boat services), all forms of urban public transport (metro, suburban train, tram, trolleybus, bus and all special transport (e.g. funicular)) and passenger cars. The dataset excludes taxi and ride-haling. In terms of passenger km, however, they represent a fraction of the total transport volume at the national level. Also, not included are walking and cycling. All changes in mobility were calculated as a change compared with 2020 Q1.

For comparison, Google and Facebook mobility data were also averaged on a quarterly basis, compared to Q1 2020. Google mobility data captures the changes of the entire period measured to a five-week period of January 3–February 6, 2020. From this, the changes compared with the mobility of 2020 Q1 were calculated for the entire period. For Facebook data February 2020 was the baseline, and from the dataset, the average change compared to 2020 Q1 was calculated

The results in Figure 5. show that compared to official statistics, tech companies' data underestimated the decline in mobility at the beginning of the COVID-19 pandemic, but underestimated the rebound after 2021 Q3.

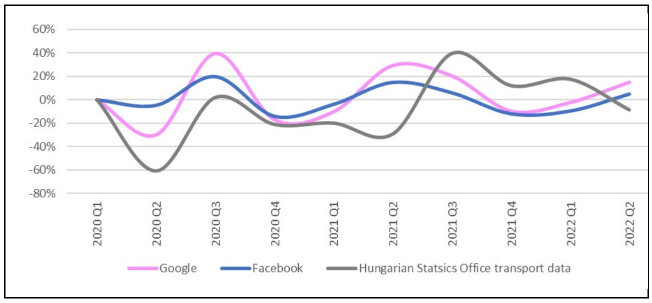

Figure 5. Quarterly changes of mobility by data source - compered to 2020 Q1 (%)

The correlation between the Hungarian transport dataset and mobility reports of tech companies is low. For Google data, the correlation is 0.44, and for Facebook, it is marginal 0.06. Between Google and Facebook data, the correlation is 0.88; therefore, it is strong. This could indicate that similar people use the two services and share mobility data with tech companies in Hungary.

6. Discussion

The analysis used in this study highlights only some aspects of the limitations of mobility data provided by Google and Facebook. The major limitation is the not sufficient information on what data these tech companies provided. As digitalization is advancing further, we will increasingly rely on data sources of tech companies, big datasets, for which validation, background, and metadata will be scarce. However, this should not discourage scientists from using any novel dataset; however, limitations and reliability concerns should attract more attention. While new, digital datasets, which are available worldwide, are very practical to use, the much more demanding data collection of more traditional data sources should also not be pushed to the background. In addition, the new datasets should be validated using real-life and/or traditional data sources.

The use of mobility data provided by tech companies was of special interest because, in many countries, it had a direct impact on public policies introduced by governments. The use of data for public policy provided by private corporations, without the possibility of third-party verification, raises questions about the potential influence of these companies on public discourse and public policies. Conversely, this case also demonstrated that, in certain situations, tech companies can react and provide information faster than governments and international institutions.

This paper highlights that the mobility databases of Google and Facebook are imprecise based on the evidence, but we were not looking into the causes of this. There are several possibilities. For instance, data quality of published tech company mobility reports could be impacted by the different data protection regulations in different regions and countries. The European Union has stricter data protection regulations than most other countries, which could have had an impact on the results.

In this analysis, the effect of changing the modal share was excluded. Understanding mobility changes during a pandemic in the future or other emergencies could be done best, if statistical offices, PTOs, and PTAs look for novel ways to publish live or almost live data on public and individual means of transport. Most of the required information is already available; however, an internationally recognized methodology and metadata would be the most adequate. Tech companies should consult professionals to validate their methodology and acquire a deeper understanding of the fields in which they lack in-depth expertise.

As tech companies possess ever greater amounts of data, researchers will be increasingly reluctant to use their databases. The sharing of information by these companies is mostly on an ad hoc basis, and the rules of access are blurred, making it very complicated to validate these non-public datasets. Regulation of public and/or scientific access at the international level could help overcome this phenomenon. Sharing detailed information about methodology, data collection methods, validation, and basic sociodemographic data by tech companies could bolster the credibility of these data sources. In addition, a repository of published datasets for scientific data could facilitate equal access.

Finally, an exploration of potential legislative frameworks or industry standards to govern the provision of public data by tech companies may be warranted. Aligning data reporting practices with established standards could foster a more reliable landscape for scientific analyses. Regulation and higher transparency could prevent the dissemination of less reliable information, which can have a direct impact on public opinion and discussion.

In summary, delving into these multifaceted avenues for future research can significantly elevate the reliability and validity of mobility data provided by tech companies in scientific investigations.

6. Conclusions

Tech companies provided mobility data during the COVID-19 pandemic on the basis of the usage of their platforms. This data sharing was a unique and, until now, a one-off possibility to use the information collected by them for scientific analysis and public policy. The datasets were easily accessible, updated weekly, and provided strongly needed and desired almost live data. However, little emphasis was placed on the reliability and validity of the data. Hundreds of scientific analyses were created without highlighting the constraints and limitations of the datasets.

By comparing the Google and Facebook mobility datasets, it was shown that they are incoherent and that the discrepancy greatly varies by region and country. The comparison of Google and Facebook mobility data with statistical data and precise passenger counting of public transport companies and transport authorities shows that the provided data are not representative of real mobility changes. Google mobility reports showed a higher correlation with PTO/PTA registered transport demand changes than Facebook. Based on the findings of this article, greater caution should be exercised in utilizing data and information provided by tech companies in scientific research and government policies, as the article demonstrated that mobility data from Google and Facebook cannot be considered representative of real mobility changes.

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Unveiling Roadway Environmental Characteristics that Influences Road Traffic Crashes occurrences and Fatality in Oyo State Nigeria

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Abstract This study sought to ascertain the effect of environmental highway elements on traffic crashes. Using statistics on traffic accidents from the Federal Road Safety Corps (FRSC) for the years 2020–2022, a study was carried out in the Nigerian state of Oyo. Blackspots along different routes were discovered from the record, along with the kind of collision and environmental conditions on the roadway. Environment factors like the accident site, weather, highway flaws and geometry, and road surface condition contributed to blackspots. 9886 traffic crashes were included in the analysis. Compared to 3.19% and 3.57% at dawn and sunset, respectively, the proportion of traffic crashes resulting in injuries was 12.60% and 12.97%. When it comes to road traffic collision occurrences, crash scene light and roadway segment geometry have a stronger significant link than road surface quality, which has a very weak significant relationship with road hazardous environmental elements. The degree of light at the collision site, which is symbolised by sunrise and sunset, exacerbates the severity. misty, foggy, stormy, or wet, four-way intersections, limited or single lanes, flat or straight roads, lack of a conventional road guard, and insufficient road shoulder Pot holes and dry or wet patches on the road have p values that are less than the alpha set value of 0.005, making them statistically significant factors in fatality and injury crashes.

Keywords Traffic crashes, Environmental factors, Road geometry, Crash severity, Road conditions

JEL R41

1. Introduction

In road traffic collisions (RTCs), around 50 million people are wounded and 1.2 million people are killed globally each year, according to the World Health Organisation's (WHO) global status report on road safety (Penden et al., 2004). Researchers have long been interested in the impact of the environment on a number of health conditions. For example, it is well recognised that climatic conditions may affect people's health. An increasing number of studies have examined the connection between environmental variables and RTCs in the field of RTCs (Toro et al., 2009). (Alkaabi, Dissanayake, and Bird, (2011); Al Marzooqi, Badi, and Jack, 2010). In several papers, environmental factors such as weather and other seasonal influences were analysed together with traffic volume, pedestrian volume, and route geometry. Donroe et al. (2008), Al Marzooqi, Badi, and El Jack (2010)). Others spoke about how RTCs are affected by daytime and nighttime light conditions. Numerous studies have examined various facets of RTCs. On the other hand, there aren't many published studies discussing how environmental variables affect RTCs. The current study set out to ascertain the relationship between environmental variables and RTCs in Nigeria in order to shed light on the possible impact of these factors on RTCs and enhance preventative efforts.

2. Methodology

Road Safety International 2020 states that, in the 1980s, when the Victorian blackspot programme began in Australia, a site had to have 12 fatalities in three years in order to be classified as a "blackspot." Today, that need is reduced to three fatalities in five years. A blackspot is an area where there are a lot of fatal, major, or minor collisions. It might be a stretch of road or a junction (road segment). The most crucial information used to achieve the accomplishments consists of:

- Where the crash occurred (location)
- When (time) it happened (day/night) revealing scene light
- The road users involved (causality level)
- Conditions at the time were rain, wind, fog, and sun
- Roadway characteristic assessment.

2.1. Research Design

A descriptive, correlational research design was employed for this investigation. This made it possible for the researcher to collect the necessary data, understand how road safety is managed, and identify any possible connection between the state of Oyo's traffic crashes and the state's road environment.

2.2. Study Area

The approximate location of Oyo State is 7° 22' N and 3° 58' E on the Greenwich Meridian. That being said, the region, often known as the metropolitan area, lies between latitudes 7°15' and 7°30' north of the equator and longitudes 3°45' and 4°00' east of the Greenwich Meridian. It is located in the southwest of the nation and is bordered to the east, north, and south by Osun State, Lagos State, and Kwara State. Oyo State is one of the states that form the Nigerian Federation. It's around 145 kilometres northeast of Lagos.

Lagos' most direct connection forms its western boundary with the Republic of Benin; nonetheless, the city is directly connected to several locations in Nigeria by a network of highways, trains, and air lines. Ibadan is a key break-bulk point for trading products from the southwest to the north and from the north to the southwest, and it is traversed by the railway that leads to the northern states.

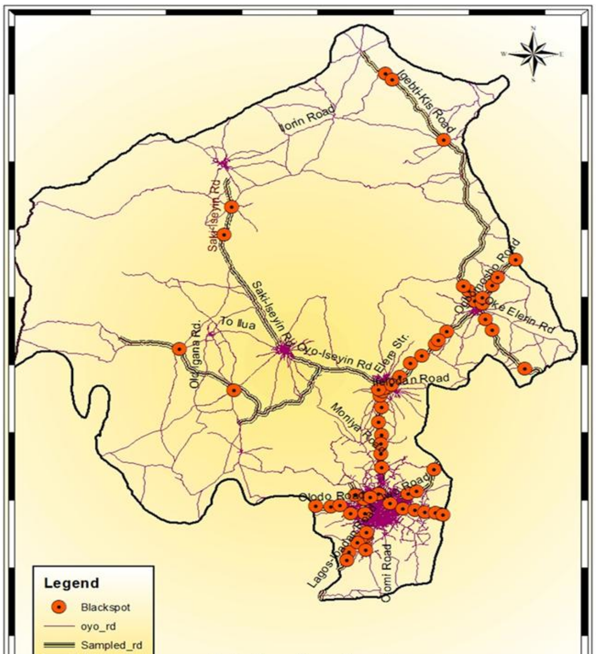

Figure 1. Map of Oyo state showing the blackspots

In descending order of significance, Oyo State residents engage in trade, work in public service, and agriculture. The sheer amount and variety of food product demand fueled the desire for agricultural output in the city's environs. A large number of city dwellers work in agriculture. Furthermore, the land left over after urbanisation has been turned into gardens known for their biological richness and variety due to people' expertise and economic demands. Cassava, maize, and vegetables such as Chinese spinach, okra, aubergine, cucumber, tomatoes, and pepper are the main crops grown in Ibadan. Socioeconomic facilities in Ibadan include marketplaces such as Alesiloye and Oja-oba, retail malls, and fast-food restaurants spread across the city, as well as an excellent road network that facilitates simple movement of people and products. Fig 1.

2.3. Method of Data Gathering

This includes gathering feedback from the blackspot locations determined by the FRSC Oyo State Sector, as shown in Fig. 1. This research is primarily concerned with the roads that the FRSC covers in Nigeria's Oyo State in order to evaluate the state of the road in connection with determining the environmental factors that encourage traffic accidents along the different road segments. The Federal Road Safety Corps (FRSC) traffic collision database in Oyo state sector 2020–2022 served as the researcher's primary source of data. Georeferenced maps of Oyo State, road network maps, satellite images (Landsat and Google Maps), and data from road segments with identified traffic crash blackspots were collected during a field survey. These locations were measured, and the picked coordinates were recorded using a handheld GPS device to make them easy to recognise in a GIS environment.

2.4. Sources and Data Collection Instruments

The data collection processes are as follows:

1. Personal Observation: The researcher conducted a field survey of the identified road segments in the study area in order to identify these road segments with traffic crash black spots, observe their unique physical properties, and create an attribute table for the various road segments.

2. Secondary Data

The data used for this study include the satellite imagery of Landsat and Google Earth with spatial resolutions of 30 and 5 metres, respectively, which were acquired and used to extract the route for the study area, the coordinates of the crash segments with the aid of GPS, and the crash record of the study area obtained from the Federal Road Safety Corps (FRSC) with the attribute data below:

1. Time of occurrence of crash
2. Location or route of the crash
3. Number of vehicles involved
4. Type of crash (fatal, severe, major, or minor)
5. Causes of the crash
6. The number of people involved in the crash

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3. Data Analysis and Results

The figure 2 shows the roadway environmental characteristics, sub-elements, number of crashes, injuries, deaths, and fatalities as reported by the FRSC.

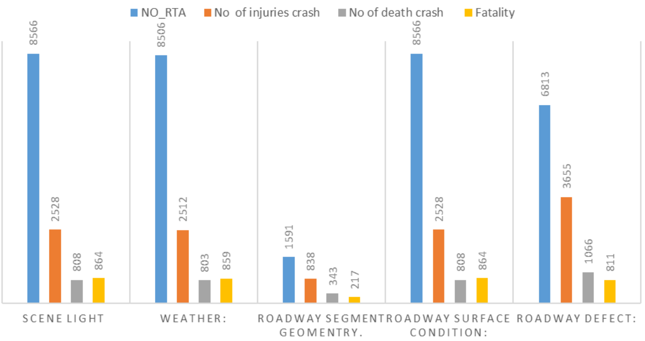

Figure 2. Number of crash related to each environmental factors

3.1. The Roadway Environmental Factors and Roadway Traffic Crash

H_1: There is no significant impact of roadway environment factors on traffic crash occurrence.

The chart in Fig. 2 shows that roadway defects produce the highest level of injury and death crashes, even with the second-lowest occurrence of roadway traffic crashes in the study area. Other influencers of roadway traffic crashes are the time of crash (scene light) and roadway surface condition, which have equal contributions to injuries and deaths. Roadway segment geometry has the lowest influence on causing roadway traffic crashes, with the lowest injuries and deaths associated. Weather is associated with the second highest roadway traffic crash occurrence and the third highest injury level of death crash.

The statistical assessment of the effect of roadway environmental factors on roadway traffic crash occurrences is to statistically evaluate the significance of the relationship between roadway traffic crash occurrence and roadway environment using multiple regression analysis.

Multiple Regression Analysis

Multiple regression is a statistical method used to examine the relationship between a dependent variable and two or more independent variables. It allows us to understand how the independent variables collectively relate to or influence the dependent variable. By controlling for the effects of other variables, multiple regression helps us identify which independent variables have a significant impact on the dependent variable and to what extent. According to Gulden, Kaya Uyanik and Nese Guier (2013) found that it can be used to assess the importance of the independent variable in a given regression equation. In this study, multiple regression is used with a view to finding out the level of importance or contribution of the independent variables (time of crash, roadway alignment, and roadway surface condition) to road traffic crash occurrence by analysing the beta coefficients to show the importance of each coefficient, as exemplified by Kaya Uyanik and Nese Guier (2013). The magnitude indicates the size of the impact that a specific independent variable has on the dependent variable. A larger absolute beta coefficient value suggests a stronger influence. While statistical significance is determined by the p-values associated with the beta coefficients. Multiple regression model is stated as below (see Table1).

Table 1. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.751a	0.564	0.430	0.290
Change statistics				
R Square Change	F Change	df1	df2	Sig. F Change
0.564	4.203	4	13	0.021

The R-value represents the correlation between the dependent and independent variables, which is 0.751, which implies that there is a 75.1% correlation between the dependent (roadway traffic crash occurrence) and independent variables, with the R square value at 0.564, meaning that the model explains 56.4% of the variance in road traffic crash occurrences. While the adjusted variable of 0.430 implies that 43% of the variance of the dependent variable is explained by the independent variables.

Table 2. ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1					
Regression	1.410	12	0.352	4.203	0.021
Residual	1.290	13	0.084		
Total	2.500	17			

a. Predictors: (Constant), Roadway segment geometry. Roadway surface defect, Road Surface Condition, Time of crash

b. Dependent Variable: Road traffic crash.

Important Model: We reject the null hypothesis because the p-value (0.021) is less than the standard alpha threshold of 0.05, which shows that at least one of the independent variables has a significant relationship with the dependent variable, indicating that the regression model strongly predicts the dependent variable. Overall Fit: The large F-value of F (4.13) = 4.203 suggests that the model accounts for a sizable percentage of the variation in the dependent variable (road traffic crash). The multiple regression model is statistically significant, as indicated by the ANOVA table, which suggests that the independent variables together offer a strong match for predicting the dependent variable at R square = 0.564, indicating that the model explains 56% of the variance in road traffic crash occurrence.

The unstandardized coefficient, or B, is 0.762. This is the projected value of the dependent variable when all independent variables are zero, or the intercept of the regression line. 1.500 is the t-value. To see if the constant deviates noticeably from zero, use this value. P-value (signature): 0.158. This result indicates that the constant is not statistically significant because it is bigger than 0.05. Time of crash B: 0.634. Keeping all other factors fixed, the dependent variable is predicted to grow by 0.634 units for every unit increase in crash time.

Table 3. Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	0.762	0.508		1.500	0.158	-0.336	1.860
Time of crash	0.634	0.197	0.851	3.219	0.007	0.209	1.059
Road Surface Condition	-0.757	0.279	-0.677	-2.716	0.018	-1.360	-0.155
Roadway defect	0.192	0.048	1.060	4.005	0.001	0.088	0.295
Roadway geometry	0.039	0.049	0.159	.798	0.439	-0.067	0.145
Weather condition	0.211	0.38	1.099	3.061	0.021	0.071	0.311

Dependent Variable: Road traffic crash.

The unstandardized coefficient, or B, is 0.762. This is the projected value of the dependent variable when all independent variables are zero, or the intercept of the regression line. 1.500 is the t-value. To see if the constant deviates noticeably from zero, use this value. P-value (signature): 0.158. This result indicates that the constant is not statistically significant because it is bigger than 0.05. Time of crash B: 0.634. Keeping all other factors fixed, the dependent variable is predicted to grow by 0.634 units for every unit increase in crash time.

The standardised coefficient, or beta, is 0.851. This suggests that there is a significant positive correlation between the dependent variable (road traffic crash occurrence) and the time crash t-value: 3.219. This figure determines whether the coefficient deviates noticeably from zero. Significance: 0.007. This number is less than 0.05, indicating statistical significance for the time of crash for B, the 95% confidence interval is 0.209–1.059.

Road surface condition, B: -0.757. The dependent variable (road traffic crash) is predicted to fall by 0.757 units for every unit increase in the road surface condition (assuming higher values imply poorer conditions), keeping all other factors constant. Beta is -0.677. This suggests that the dependent variable and road surface condition have a strong negative connection. t-value:-2.716. Significance: 0.018. The road surface condition is statistically significant because this value is smaller than 0.05. B's 95% Confidence Interval: -0.155 to -1.360.

Roadway defect: B: 0.192. Keeping all other factors equal, the dependent variable (road traffic crash) should rise by 0.192 units for every unit increase in highway defect. Beta is 1.060. This suggests that there is a highly significant positive correlation between the dependent variable and the roadway defect. 4.005 is the t-value. Significance: 0.001. Roadway defect is statistically significant since this value is smaller than 0.05. For B, the 95% confidence interval is 0.088–0.295.

Roadway geometry: B is 0.039. Keeping all other factors fixed, the dependent variable (road traffic crash) is predicted to rise by 0.039 units for every unit increase in roadway geometry. Beta: 0.159. This suggests that the roadway geometry and the dependent variable have a weakly positive correlation (t-value: 0.798). Significance: 0.439. The roadway geometry is not statistically significant, as this value is more than 0.05. -0.067 to 0.145 is the 95% confidence interval for B. Zero is included in this interval, confirming its absence of importance.

Weather Condition B is 0.211: Keeping all other factors fixed, the dependent variable (road traffic crash) is predicted to rise by 0.211 units for every unit increase in weather condition. Beta = 1.099: This suggests that there is a highly significant positive correlation between the dependent variable and the weather condition. 3.06 is the t-value: Significance: 0.021: The weather condition is statistically significant since this value is smaller than 0.05, for B = 95%. The confidence interval is 0.071–0.311.

Significant Predictors: The dependent variable (road traffic crash) may be statistically predicted by the time of the crash, roadway condition, and roadway defects. Non-Significant Predictors: There is no statistically significant correlation between the roadway geometry and the constant.

Connections: The dependent variable (road traffic crash) has a positive correlation with the time of the crash, weather condition, and road defect. There is a negative correlation between the dependent variable (road traffic crash) and road surface condition. Repairing road imperfections and enhancing road surface conditions may have a big effect on road traffic crashes.

In testing the null hypothesis, which states that "there is no significant effect of roadway environment factors on traffic crash occurrence," looking at the elements of the roadway environmental factor, which are time of crash, road surface condition, Roadway defect, Roadway geometry and weather condition as the independent variables. We can conclude that there is significant evidence to reject the null hypothesis that states that there is no significant effect of roadway

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environment factors on traffic crash occurrence, and hence state that "there is a significant effect of roadway environment factors on traffic crash occurrence.".

3.2. Factors Causing High Odd of Death and Injuries Crash

There is no significant effect of the elements of roadway environmental factor on roadway traffic crash resulting to death and injuries.

The road way environmental factors refers to the prevailing unique conditions on the road that have an impact on traffic crash. Some of these variables have been identified by Kamran et, al (2019). In this study there are five road crash related environmental factors considered in the study area Table 4 show the various environmental factors and the component variable within them and the number of crash related to each environmental factors respectively.

Table 4 contains the environmental factors and the elements within the factors in relation to the number of crashes and the type of crash. The table is important in the quest to find the odd roadway traffic crash that has a chance to produce death or injury. Multinomial logistic regression was then conducted.

Table 4. No of crash related to each environmental factors

N	Elements	Factors	NO. RTC	injuries crash	death crash	Serious crash	minor Crash
1	Time of Crash	Day Sunrise	3571	1246	315	353	1657
		Night Sunset	4995	1282	493	511	2709
2	Weather	Clear	384	168	50	58	108
		Cloudy	282	112	38	54	78
		Foggy	1057	184	380	98	395
		Stormy/rainy	1783	748	335	349	351
3	Roadway segment geometry	4-way intersection	266	110	27	29	100
		Narrow single lane	962	155	92	95	620
		Roundabout	229	114	35	43	37
		Straight flat Up hill	647	424	182	40	1
		Straight/ curved road	87	35	7	7	38
4	Roadway surface condition	Dry	229	114	35	43	37
		Pot holes	29	12	4	4	9
		Wet	817	84	169	308	256
5	Roadway defect	Defective/ No lighting	1947	627	139	141	1040
		Inadequate road shoulder	494	117	158	169	50
		Lack of standard road guard	15	5	4	4	2
		Partial road collapse	1706	182	465	172	887

Source: Author's Compilation, 2023

The hypothesis investigating the substantial link between roadway traffic crash fatalities (injuries and deaths) and roadway environment parameters was prompted by the knowledge that roadway environmental elements have a variety of effects on the fatality of road traffic crashes. A binomial logistic regression model was created to assess the odds and probability of the fatality of a crash under the combination of various roadway environmental factors, allowing the researcher to determine which of the component variables of the roadway environment factors in this study contributes the most to the fatality of roadway traffic crashes (death and injuries).

Binomial Logistic Regression

From the predictor table (Table 5), it is observed that the roadway environmental factors predators have no significant association with roadway traffic crash fatalities.

Table 5. Predictors' Unique Contributions in the binomial Logistic Regression

Predictor	**x**	**df**	**p-value**
Time of crash	0.005	1	0.94
Weather	2.173	1	0.34
Road Segment alignment	1.773	1	0.18
Road Surface Condition	0.096	1	0.76
Roadway Defect	1.425	1	0.53

However, with further investigation into the elements within these environmental factors, applying multinomial logistic regression, we are able to ascertain the odds of death and injury fatalities shown in Table 6.

Table 6. Coefficients of factors on road traffic crash fatality

Factor	**Coefficient (β)**	**Odds Ratio (OR)**
Night Sunset	0.5	e0.5≈1.65e^{0.5} \approx 1.65e0.5≈1.65
Cloudy	0.2	e0.2≈1.22e^{0.2} \approx 1.22e0.2≈1.22
Foggy	1.0	e1.0≈2.72e^{1.0} \approx 2.72e1.0≈2.72
Stormy/Rainy	0.7	e0.7≈2.01e^{0.7} \approx 2.01e0.7≈2.01
Narrow Single Lane	0.3	e0.3≈1.35e^{0.3} \approx 1.35e0.3≈1.35
Roundabout	0.1	e0.1≈1.11e^{0.1} \approx 1.11e0.1≈1.11
Straight Flat Up Hill	0.6	e0.6≈1.82e^{0.6} \approx 1.82e0.6≈1.82
Straight/Curved Road	-0.1	e−0.1≈0.90e^{-0.1} \approx 0.90e−0.1≈0.90
Pot Holes	0.4	e0.4≈1.49e^{0.4} \approx 1.49e0.4≈1.49
Wet	0.5	e0.5≈1.65e^{0.5} \approx 1.65e0.5≈1.65
Inadequate Road Shoulder	0.7	e0.7≈2.01e^{0.7} \approx 2.01e0.7≈2.01
Lack of Standard Road Guard	1.2	e1.2≈3.32e^{1.2} \approx 3.32e1.2≈3.32
Partial Road Collapse	1.5	e1.5≈4.48e^{1.5} \approx 4.48e1.5≈4.48

Source: Author's Compilation, 2023

Binomial logistic regression is used when the outcome variable is not more than two categories of predictors, These odds ratios compare the odds of an event occurring (roadway traffic crash) given a factor to the odds of an event occurring in the absence of that factor. The fatality of a road traffic crash in this study is defined by the number of deaths and injuries in a crash at a given location and at a particular time. Each coefficient βi represents the change in the log odds of the dependent variable being 1 for a one-unit change in the corresponding predictor Xi, holding all other predictors constant. The odds ratio can be computed as $e^{\beta i}$. An odds ratio greater than 1 indicates an increase in the odds of the outcome with an increase in the predictor, while an odds ratio less than 1 indicates a decrease.

Interpretation

Time of Crash with regards to Night Sunset (OR = 1.65), deaths crashes occurring during Night Sunset are 1.65 times more likely to result in death compared to those occurring during Day Sunrise. This indicates that night-time conditions might be more hazardous, leading to more severe outcomes. However injuries conversely, crashes during Night Sunset are less likely to result in injuries compared to Day Sunrise. This suggests that while night-time crashes are less frequent, they tend to be more severe when they do happen.

In the case of the Weather, Cloudy (OR = 1.22), deaths crashes occurring in cloudy weather are 1.22 times more likely to result in death compared to clear weather. Cloudy conditions might reduce visibility or make road conditions slightly more dangerous. In the case of injuries crashes in cloudy weather are less likely to result in injuries compared to clear weather. This indicates that crashes in cloudy conditions are somewhat more severe.

For Foggy (OR = 2.72), deaths crashes occurring in foggy conditions are 2.72 times more likely to result in death compared to clear weather. Fog significantly reduces visibility, leading to more severe accidents. Injuries crashes in foggy conditions are much less likely to result in injuries compared to clear weather. This shows that foggy conditions greatly increase the severity of crashes.

While stormy/Rainy (OR = 2.01), deaths crashes occurring in stormy or rainy conditions are 2.01 times more likely to result in death compared to clear weather. Wet and slippery roads contribute to more severe accidents. While injuries crashes in stormy or rainy conditions are less likely to result in injuries compared to clear weather, indicating a higher severity of crashes.

Whereas roadway segment geometry, narrow single lane (OR = 1.35), deaths crashes occurring on narrow single lanes are 1.35 times more likely to result in death compared to those occurring at 4-way intersections. Narrow lanes can be more dangerous due to limited space for maneuvering. Injuries crashes on narrow single lanes are less likely to result in injuries compared to 4-way intersections. This implies that crashes on narrow lanes tend to be more serious.

With regards to roundabout (OR = 1.11), deaths crashes occurring in roundabouts are 1.11 times more likely to result in death compared to 4-way intersections. Roundabouts might cause confusion, leading to more severe crashes. Injuries crashes in roundabouts are slightly less likely to result in injuries compared to 4-way intersections, suggesting a slightly higher severity.

For a straight flat uphill (OR = 1.82), deaths crashes occurring on straight flat uphill segments are 1.82 times more likely to result in death compared to 4-way intersections. The higher speeds possible on these segments can contribute to more severe crashes. Injuries crashes on straight flat uphill segments are less likely to result in injuries compared to 4-way intersections, indicating a higher severity of crashes.

Relating with straight/curved road (OR = 0.90), deaths crashes occurring on straight or curved roads are 0.90 times as likely to result in death compared to 4-way intersections, meaning they are less likely to be fatal. Injuries crashes on straight or curved roads are more likely to result in injuries compared to 4-way intersections, suggesting that these crashes are less severe.

Concerning roadway surface condition, Pot Holes (OR = 1.49): Deaths crashes occurring on roads with pot holes are 1.49 times more likely to result in death compared to those occurring on dry roads. Pot holes can cause vehicles to lose control, leading to severe crashes. Injuries crashes on roads with pot holes are less likely to result in injuries compared to dry roads, indicating a higher severity of crashes.

In the case of wet road condition (OR = 1.65), deaths crashes occurring on wet roads are 1.65 times more likely to result in death compared to dry roads. Wet roads can be slippery and increase the likelihood of severe crashes. While Injuries: Crashes on wet roads are less likely to result in injuries compared to dry roads, suggesting that crashes in wet conditions are more severe.

Regarding roadway defect, inadequate Road Shoulder (OR = 2.01), deaths crashes occurring on roads with inadequate road shoulders are 2.01 times more likely to result in death compared to roads with no defects. Lack of proper shoulders can prevent safe recovery if a vehicle goes off the road. Injuries crashes on roads with inadequate road shoulders are less likely to result in injuries compared to roads with no defects, indicating higher severity.

About lack of standard road guard (OR = 3.32), deaths crashes occurring on roads lacking standard road guards are 3.32 times more likely to result in death compared to roads with no defects. Road guards prevent vehicles from veering off the road or into oncoming traffic. Injuries crashes on roads lacking standard road guards are significantly less likely to result in injuries compared to roads with no defects, indicating much higher severity.

In the case of partial road collapse (OR = 4.48), deaths crashes occurring on roads with partial road collapse are 4.48 times more likely to result in death compared to roads with no defects. Road collapses can cause severe crashes due to sudden loss of road structure. Injuries crashes on roads with partial road collapse are substantially less likely to result in injuries compared to roads with no defects, indicating extremely high severity.

4. Conclusions

Odds Ratios > 1: Indicates an increased likelihood of death and a decreased likelihood of injury. Factors such as nighttime crashes, adverse weather conditions (foggy, stormy/rainy), and poor roadway conditions (narrow lanes, pot holes, inadequate road shoulders) significantly increase the likelihood of fatal crashes, making injuries less likely in comparison.

Odds Ratios < 1: Indicates a decreased likelihood of death and an increased likelihood of injury. For example, crashes on straight or curved roads are less likely to result in death, meaning they are more likely to result in injuries compared to other road types.

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Advancing Business Strategy and Innovation in the Digital Age

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Abstract This study synthesizes current research on innovation, business models, and digital transformation, focusing on their intersection to address emerging challenges in sustainability and ethical considerations. This paper develops actionable insights for aligning digital strategies with organizational capabilities using a hybrid approach informed by multiple frameworks. Key findings reveal the role of dynamic capabilities and ethical dimensions in fostering competitive advantage and sustainable growth. However, the study is limited by its reliance on secondary data, suggesting that future research could enhance the framework through primary data collection and cross-industry comparisons. This framework aims to guide decision-makers in adapting to technological advancements while maintaining ethical integrity.

Keywords Digital transformation, innovation, business models, dynamic capabilities, strategic alignment, ethical decision-making

JEL O39, Q01, Q56

1. Introduction

The rapid evolution of technology and its pervasive integration into business has transformed the operational, strategic, and societal paradigms of organizations. This article explores the interplay between innovation, business models, and digital transformation, highlighting their critical roles in fostering organizational resilience and sustainability. This paper aims to propose a multidimensional framework that integrates these domains with ethical considerations by addressing gaps in current research.

2. Theoretical Background

The theoretical foundation of this study examines the interplay of three critical dimensions shaping modern organizations: innovation, dynamic capabilities, and ethical considerations in digital transformation. First, the exploration of innovation and business models provide insight into how firms create and deliver value in rapidly changing markets.

Next, the role of dynamic capabilities is analyzed to understand how organizations adapt their strategies to evolving environments. Finally, ethical considerations are discussed to highlight the importance of responsible innovation in addressing societal and technological challenges.

2.1. Innovation and Business Models

Innovation has long been recognized as a key driver of organizational growth and competitive advantage. According to the Oslo Manual, innovation can be classified into product, process, marketing, and organizational dimensions. Each of these plays a crucial role in adapting to evolving market demands. For instance, product innovation involves introducing new or significantly improved goods or services, while process innovation focuses on optimizing production and delivery systems. Both forms of innovation are critical in maintaining relevance in dynamic markets. [1]

Business models serve as the blueprint for creating and delivering value. The Business Model Canvas, a widely accepted framework, outlines nine key components that enable organizations to define how they generate revenue while addressing customer needs. In the digital era, traditional business models are undergoing significant transformations. Organizations increasingly adopt platform-based and subscription-based models, reflecting shifts in consumer behavior and technological advancements. A dynamic approach to business models, integrating innovative solutions such as virtualization, cloud computing, and data-driven insights, is essential for sustaining competitiveness. [1,2]

The relationship between innovation and business models is symbiotic. Effective innovation informs the development of agile business models, while robust business models provide the structural foundation for scaling innovative ideas.

This interdependence highlights the necessity of integrating innovation strategies with business model evolution. [2]

2.2. Dynamic Capabilities and Strategy Alignment

Dynamic capabilities theory provides a critical lens for understanding how organizations adapt to rapidly changing environments. This theory emphasizes three core capabilities: sensing opportunities, seizing them through timely action, and transforming internal resources to align with external demands. These capabilities enable organizations to remain agile, ensuring that strategic goals are consistently aligned with market realities. [2,3]

Strategic alignment involves synchronizing organizational objectives with technological advancements. This alignment is increasingly vital as digital strategies merge with traditional business strategies. Studies suggest that organizations that align IT strategies with broader business goals experience enhanced performance and resilience. For instance, aligning digital capabilities with customer-centric approaches allows firms to respond effectively to changing preferences and market conditions. [4]

The concept of alignment is not static but dynamic, requiring continuous adaptation to both internal and external changes. Organizations must regularly reassess their capabilities, resources, and strategies to ensure they remain aligned with emerging trends and challenges. [5,6]

2.3. Ethical Dimensions in Digital Transformation

As digital technologies become more embedded in organizational processes, ethical considerations have gained prominence. The integration of AI, IoT, blockchain, and big data has introduced a range of ethical challenges, from data privacy and security to algorithmic biases and societal impacts. Addressing these challenges is essential for maintaining trust and ensuring that digital transformation contributes positively to society. [7,8]

Data privacy is a particularly pressing issue, with consumers and regulators demanding greater transparency and control over how personal information is collected, stored, and used. Ethical lapses in this area can result in reputational damage, regulatory penalties, and loss of consumer trust. Organizations must implement robust data governance frameworks to ensure compliance and build stakeholder confidence. [7]

Algorithmic decision-making, another cornerstone of digital transformation, presents ethical dilemmas related to fairness and accountability. Biases in AI systems can perpetuate inequality, leading to adverse social consequences. Organizations are increasingly called upon to adopt transparent and inclusive approaches to AI development and deployment. [7,8]

Beyond compliance, ethical considerations also provide a competitive advantage. Companies that prioritize ethical practices are better positioned to attract socially conscious consumers and investors. The integration of ethical considerations into strategic planning is thus both a moral imperative and a business opportunity. [8]

This theoretical background highlights the complexity and interdependence of these dimensions, offering a comprehensive lens through which organizations can navigate the challenges and opportunities of the digital era. By synthesizing insights from these domains, this study contributes to the development of actionable strategies that balance innovation, alignment, and ethics.

3. Objectives

In an era defined by rapid technological advancements, organizations face unprecedented challenges and opportunities. This study aims to address critical aspects of navigating the digital landscape through the following primary research objectives:

- **to explore the alignment of business strategies with digital transformation:** understanding how organizations can effectively integrate digital strategies with their overarching business goals to achieve efficiency and adaptability**,**
- **to assess the role of innovation in sustaining competitive advantage:** investigating the impact of innovation in driving differentiation, creating values streams, and maintaining market relevance in the digital economy**,**
- **to examine ethical challenges arising from digitalization and propose strategies for their mitigation:** identifying ethical dilemmas such as data privacy and algorithmic biases while developing strategies to address these concerns and foster stakeholder trust.

The research objectives, assumptions, and questions are shown in the following Table 1.

Table 1. Research objectives

Research objectives	Research assumptions	Research questions
RO1: Alignment of Business Strategies with Digital Transformation	**RA1:** Businesses struggle to adapt strategies to digital trends, leading to inefficiencies and missed opportunities	**RQ1:** How can organizations align their strategies with digital transformation to ensure efficiency and growth?
RO2: Role of Innovation in Sustaining Competitive Advantage	**RA2:** Firms face challenges in maintaining relevance and market position admits technological advancements	**RQ2:** What are the most effective innovation practices for sustaining competitive advantage in a digital economy?
RO3: Ethical Challenges in Digitalization and Their Mitigation	**RA3:** Organizations encounter ethical dilemmas, including data privacy and fairness, due to digital transformations	**RQ3:** How can ethical challenges in digitalization be identified and mitigated effectively?

4. Methodology

This study employs a qualitative, multi-case research approach to explore the complex relationships between digital transformation, innovation, and ethical considerations. The methodology is designed to integrate theoretical insights and practical applications, ensuring a comprehensive response to the study's objectives. The research is structured around a combination of a detailed literature review, case study analysis, and the development of an integrated framework.

The research begins with a thorough review of existing literature on digital transformation, innovation, and ethical challenges. Peer-reviewed journal articles, industry reports, and theoretical frameworks are analyzed to identify key trends and insights. This step provides a robust theoretical foundation for the study and highlights the relevance of strategic alignment, innovation, and ethics in navigating digital transformation.

The second phase involves analyzing case studies of organizations across different industries, with a focus on small and medium-sized enterprises (SMEs) and large corporations. These cases illustrate real-world applications of digital strategies, highlighting both successes and challenges. Specific attention is paid to how these organizations align their strategies, foster innovation, and address ethical considerations. [1,5]

Finally, findings from the literature review and case study analysis are synthesized into a multidimensional framework. This framework integrates strategic alignment, innovation, and ethical considerations to guide organizations in navigating the complexities of digital transformation. The framework is designed to be adaptable across various organizational contexts and industries. [6,7]

Table 2. Phased Methodological Approach for Exploring Digital Transformation, Innovation, and Ethics

Phase	Objective	Data Source	Outcome
Literature Review	Analyse key theories and trends in digital transformation, innovation, and ethics	Peer - review journals, academic reports	Theoretical foundation for strategic alignment and innovation
Case Study Analysis	Examine real - world applications of digital strategies and ethical practices	Case studies from SMEs and large firms	Empirical insights into successful and failed strategies
Framework Development	Synthesize findings to propose a multidimensional framework integrating innovation and ethics	Combined outputs from prior phases	Practical and adaptable strategic framework

Table 2. summarizes the key phases, objectives, data sources, and outcomes of the methodological approach. It illustrates how each phase contributes to addressing the study's research objectives.

The reliance on secondary data ensures broad coverage, but it also introduces certain limitations. For instance, secondary data may not capture the specific nuances of organizational contexts. While the framework is intended to have cross-industry applicability, some industry-specific dynamics may not be fully represented. Future research could address these limitations by incorporating primary data collection methods, such as interviews or surveys, and conducting cross-industry comparisons to validate the findings.

Ethical considerations are central to this research. All secondary sources are appropriately cited, ensuring full acknowledgment of original authors. Should future studies involve primary data collection, ethical approval would be sought to protect participant confidentiality and ensure data integrity. [8]

By combining theoretical exploration with empirical insights and organizing them into structured phases, this methodology ensures a comprehensive and actionable understanding of the critical dimensions shaping modern organizational strategies. The integrated approach lays a strong foundation for addressing the study's objectives and offers a roadmap for future research.

5. Results

The results of this study address the outlined objectives, providing significant insights into the alignment of business strategies with digital transformation, the role of innovation in sustaining competitive advantage, and the ethical challenges posed by digitalization. Each objective is examined considering the findings, demonstrating their relevance, and offering practical implications.

5.1. Strategic Alignment and Innovation

The first objective - exploring the alignment of business strategies with digital transformation, was confirmed through evidence that successful organizations prioritize the integration of digital strategies with their overarching business goals. By leveraging dynamic capabilities, such as sensing opportunities and transforming internal structures, firms enhance their ability to respond to changing market demands. SMEs, for instance, exemplify how agility and resource optimization in adopting digital tools foster competitiveness and market adaptability. Larger organizations benefit from aligning innovative solutions with existing infrastructures to improve scalability and efficiency. This finding underscores the importance of strategic alignment as a critical driver for achieving organizational resilience in the digital era. [3,4]

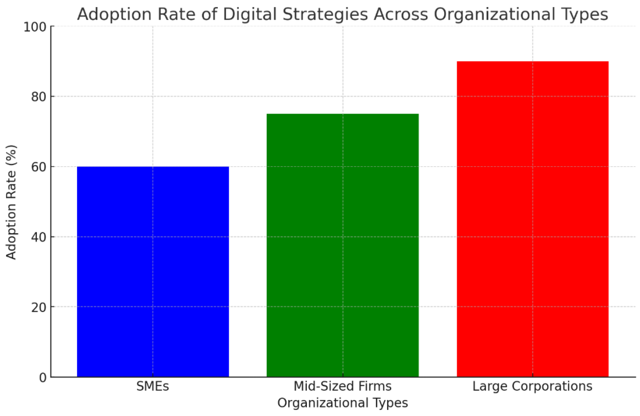

Figure 1. Adoption Rate of Digital Strategies Across Organizational Types

Figure 1. illustrates the varying adoption rates of digital strategies among different organizational types. It highlights the progressive increase in adoption from SMEs to large corporations, reflecting how organizational resources and digital readiness influence strategic implementation. SMEs demonstrate moderate adoption due to resource constraints, while larger corporations achieve higher rates owing to robust infrastructures.

5.2. The Role of Innovation in Sustaining Competitive Advantage

The second objective - to assess the role of innovation in sustaining competitive advantage, was also confirmed. The analysis highlights that innovation, particularly in integrating technologies like artificial intelligence, IoT, and blockchain, is indispensable for differentiation and creating new value streams. However, findings reveal that innovation must be strategically aligned with business objectives to mitigate risks such as resource misallocation and technological redundancies. [5]

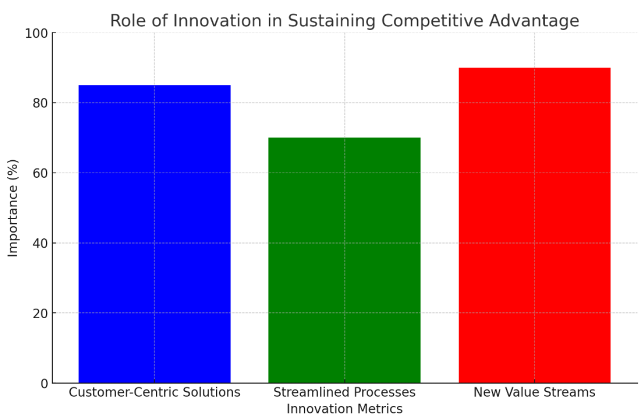

Figure 2. Role of Innovation in Sustaining Competitive Advantage

Organizations that adopt an intentional approach to innovation, focusing on customer-centric solutions and streamlined processes, are more likely to maintain a competitive edge. These insights validate the centrality of innovation in ensuring long-term growth and market relevance.

Figure 2. emphasizes the role of innovation in sustaining a competitive edge. It compares the importance of customer-centric solutions, streamlined processes, and the creation of new value streams. The findings suggest that organizations prioritizing these innovation metrics are more likely to achieve long-term market relevance and differentiation in a rapidly evolving digital landscape.

5.3. Ethical Challenges and Mitigation Strategies

The third objective - examining ethical challenges arising from digitalization and proposing strategies for mitigation was strongly supported by the findings. Ethical dilemmas such as data privacy, algorithmic biases, and societal disruptions were identified as significant concerns in the digital transformation process. Organizations that proactively addressed these issues, such as implementing robust data governance frameworks and ensuring algorithmic transparency, built greater trust with stakeholders, and achieved sustainable success. [6,7]

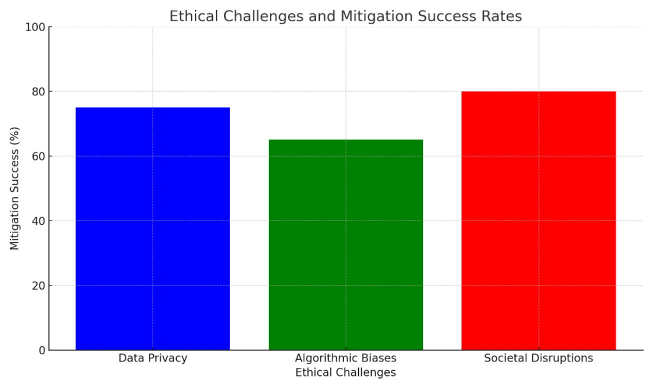

Figure 3. Ethical Challenges and Mitigation Success Rates

Figure 3. explores how organizations address ethical challenges associated with digitalization. It evaluates the success rates of mitigating data privacy issues, algorithmic biases, and societal disruptions. The findings underline the necessity of proactive measures, such as robust governance frameworks and transparent practices, to maintain trust and comply with regulatory demands.

In summary, the results confirm that the study's objectives were not only relevant but integral to understanding the complexities of digital transformation. Strategic alignment, innovation, and ethical considerations are interconnected components that collectively shape organizational success in the digital age. By addressing these objectives, this study provides actionable insights for firms seeking to thrive in a competitive and ethically demanding environment.

6. Conclusions

This study underscores the importance of integrating innovation, strategy alignment, and ethical considerations in navigating digital transformation. The multidimensional framework offers practical guidance for organizations to achieve sustainable growth while addressing societal and technological challenges. As digitalization continues to evolve, balancing innovation with ethical responsibility will be pivotal for long-term success.

For small and medium-sized enterprises, agility and resource optimization are critical, while larger organizations must focus on scalable solutions and robust governance structures. Across the board, addressing ethical challenges proactively ensures both compliance and alignment with evolving societal expectations.

By embracing this holistic approach, organizations can not only achieve competitive success but also contribute to a more sustainable and equitable digital ecosystem.

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Analysis of Consumer Visual Attention to Retail Design Elements Using Eye-Tracking Technology

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Abstract This study analyses consumer visual responses to store design elements using eye-tracking technology, focusing on identifying behavioural patterns across different age and gender groups. The primary goal was to assess how consumers respond to various aspects of the retail environment, such as price tags, promotional banners, and checkout zones. Statistical tests (Mann-Whitney U, ANOVA, and T-test) indicated no statistically significant differences between the groups observed, suggesting a need for an expanded sample size for more precise analysis and a deeper understanding of these interactions.

Keywords eye-tracking, consumer behaviour, visual attention, retail environment.

JEL M31, M37, L81, L96

1. Introduction

Analysing consumer behaviour in the sales environment is a key factor for optimising store design and increasing sales efficiency, especially in a visually stimulating environment where consumers are faced with a multitude of stimuli on a daily basis. [1] In the current literature, it is often highlighted that retail design elements such as price tags, advertising banners, product layouts or the design of the checkout area itself can significantly influence customer decision making. Price tags with clear, large print or colourful banners highlighting promotions and discounts have the potential to attract attention and encourage impulse purchases. Conversely, a cluttered or chaotic layout of the sales area can confuse and discourage consumers from buying. [2,3] Given this fact, the use of advanced technologies such as eye-tracking is becoming an increasingly common method in consumer behaviour research. [4]

The eye-tracking technology enables detailed tracking of consumers' eye movements and fixation points, providing accurate data on their visual preferences. [5] Tracking fixation points, saccades, and other aspects of visual attention enables the identification of which elements of the sales environment consumers register and respond to most intensely, which is useful for better understanding their buying behaviour. [5,6]

Based on previous studies, it appears that the impact of the sales environment may vary by demographic factors such as age and gender, supporting the need for a comprehensive analysis of differences between consumer groups. Therefore, [4,6,7] the aim of this research is to gain insight into the visual responses of different demographic groups to store design elements and to investigate whether there are statistically significant differences between gender and age groups. Thus, this research will provide new insights into how design elements can be optimized for different types of consumers. The Mann-Whitney U test, ANOVA and T-test were used to statistically evaluate the data collected, allowing for a thorough assessment of the differences between groups. This research extends the existing knowledge on consumer behaviour in retail environments and offers potential benefits for the design of effective marketing strategies in the retail industry. [8,9]

2. Methodology

The research uses eye-tracking technology to investigate in-store consumer behaviour, focusing on the analysis of visual attention of different demographic groups. Eye-tracking technology enables detailed tracking of eye movements and provides both quantitative and qualitative data that are essential for understanding which elements of the in-store environment attract consumers' attention and what factors influence their visual interaction with products and store design. [10]

The five-user rule, first proposed by Jakob Nielsen in his 2000 article "Why You Only Need to Test with 5 Users", argues that eye-tracking testing with five users can detect up to 85% of usability problems. This rule of thumb is based on a model where a single user reveals 31% of problems on average, and is applicable to qualitative testing of homogeneous focus groups. However, as Nielsen points out, when testing heterogeneous user groups or when testing quantitatively, the number of respondents needs to be increased. Research, such as a study by Laura Faulkner of AWS, has shown that groups of five users can detect only 55% to 85% of problems, while groups of ten users have detected up to 95%. [11]

In selecting the sample size, we took an approach that mitigates these limitations and included 21 respondents who were selected on the basis of age and gender. The age categories were divided as follows:

- **15-18 years** (8 respondents). This age group includes young consumers who are accustomed to modern technology and often follow current retail trends.
- **19-25 years** (12 respondents). The largest group of respondents, representing young adults who have already established some consumer habits.
- **26-50 years** (1 respondent). Older consumers who prefer the stability and simplicity of the retail environment.

In terms of gender, 9 males and 12 females were included in the sample, which allowed a comparison of gender differences in visual attention. Although the sample of respondents was relatively small, it provided a basis for initial analysis and the formulation of further recommendations.

The technological core of the research was the Screen Based Eye Tracker, which enables accurate recording of respondents' eye movements through infrared sensors and high-frequency cameras. This device was complemented by SMI's BeGaze software, which processes and visualizes the data collected by the eye-tracker. The combination of hardware and software provided a robust platform for analysing consumers' visual attention, while enabling the following metrics to be tracked and evaluated:

- **Fixations** - the number of fixations on specific elements of the sales environment. This metric reflects which elements most captured respondents' attention.
- **Fixation length** - the amount of time respondents spent on each element. A higher fixation length indicates a more intense interest in a particular element.
- **Saccades** - rapid eye movements between fixation points that show how efficiently respondents scan the sales environment and what elements they skip.
- **Dwell time** - the total time spent looking at a particular element, giving a picture of its attractiveness and ability to hold attention.

Respondents were presented with visual stimuli in the form of photographs of different parts of the stores. These photographs contained three main types of design elements that were targeted to test visual attention:

- **Price tags** - the photographs included different types of price tags with different placement (eye level, near the floor), text size, and colour design. The goal was to determine which placement and visual form of price tags most captured consumers' attention.
- **Advertising banners** - banners with different colours, graphic design and text content were tested to determine which visual features most appeal to consumers.
- **Checkout Zones** - respondents were presented with two types of checkout zones, those with a clear layout and those with lots of visual cues.

Photographs were prepared to allow A/B testing, where responses to two different design variations of the same element were compared. For example, for the checkout zone, it was analysed whether customers pay more attention to products in a zone with a clear minimalist design or, on the contrary, in a zone with a lot of visual stimuli.

Four hypotheses were defined in this research, which focused on the analysis of differences in consumer visual behaviour according to gender, age and the influence of the design of the sales environment. The hypotheses were formulated to provide answers to key questions regarding visual attention and consumer behaviour in stores. Individual hypotheses were tested using advanced statistical methods (Mann-Whitney U test, ANOVA, T-test) to test their validity.

Hypothesis 1: Difference in fixation length between men and women

(H0): There is no difference in the length of fixation on the product between men and women.

(H1): There is a difference in the length of fixation on the product between men and women.

Hypothesis 2: Difference in average fixation by age group

(H0): There is no difference in average fixation between different age groups (15-18; 19-25).

(H1): There is a difference in average fixation between different age groups (15-18; 19-25).

Hypothesis 3: The difference in the number of saccades between men and women

(H0): There is no difference in the number of saccades between men and women.

(H1): There is a difference in the number of saccades between men and women.

Hypothesis 4: Effect of checkout zone design on fixation on products

(H0): The design of the checkout zone does not affect the length of fixation on products.

(H1): The design of the checkout area has an impact on the length of fixation on products.

3. Results

This study provides initial insights into consumer visual attention within retail environments. Practical recommendations include designing clear and visually appealing price tags, simplifying checkout zone layouts, and using vibrant promotional banners to draw attention. While no statistically significant differences were found across demographic groups, these findings highlight the importance of thoughtful visual design to enhance customer experience and streamline purchasing decisions. Future research with larger sample sizes and additional demographic variables could further refine these insights and offer more targeted recommendations for retail professionals. The main objective was to test whether there are statistically significant differences between different demographic groups (men vs. women, different age categories) and how visual cues, such as checkout area design, influence consumer behaviour. Different statistical methods were used to evaluate each hypothesis, providing quantitative data for detailed comparison. Although not all differences proved to be statistically significant, the research revealed useful insights into consumer interaction with in-store design elements.

Each hypothesis was tested under the assumption of the null hypothesis (H0), which asserted that there was no statistically significant difference between the groups or design variations analysed. The alternative hypothesis (H1) assumed the opposite. The results of the testing provided a picture of whether the hypothesised differences were confirmed or rejected.

Hypothesis 1: Difference in fixation length between men and women.

To calculate the Mann-Whitney U test, we have identified 2 areas that represent the gender of the respondents, and these are male and female. The total number of respondents is 21, which is less than 30. Based on this, we have chosen an appropriate method of calculation namely Mann-Whitney U test. The values for testing the hypothesis are given in the table. Microsoft Excel software was used to calculate the values. For the calculation we have chosen 2 sexes where we have also determined the order of the elements see groups T_1 and T_2.

The function =RANK.AVG (values;1) was used to determine the order. The number of elements in group A is $n_1=12$ (number of elements of the first group) and B $n_2=9$ (number of elements of the second group). To calculate U (expected value), we plug the values into the formula U_1 and then U_2. We then use U_{min} (the smaller of U_1 and U_2). U_{crit} (tabulated value based on the number of elements from the Mann-Whitney table, alpha=0.05 for a two-tailed test)

Table 1 Results of the Mann-Whitney U test

1.	$U_1 = n_1 \cdot n_2 + \frac{n_1 \cdot (n_1+1)}{2} - T_1 = 12 \cdot 9 + \frac{12 \cdot (12+1)}{2} - 160 = 26$
2.	$U_2 = n_1 \cdot n_2 + \frac{n_2 \cdot (n_2+1)}{2} - T_2 = 12 \cdot 9 + \frac{9 \cdot (9+1)}{2} - 71 = 82$
3.	$U_1 = \min(U_1;U_2) = U_{min}\ (26\ ;\ 82) = 26$
4.	For large samples, the normal distribution of the U-value can be used as an approximation, then calculate the μ_U proportional U-value and the Z-value.
5.	Therefore, for a set with less than 30 elements in each group, the exact values that can be read from the table are used. U_{crit} in our sample example, the $U_{crit} = 26$. If $U_{min} \leq U_{crit}$; $26 \leq 26$

From the result, we can conclude that U_{min} $26 \leq U_{crit}$ 26 and this implies that we accept H0 and reject hypothesis H1: There is no difference in the length of fixation on the product between males and females.

Hypothesis 2: Difference in average fixation by age group.

The hypothesis aims to investigate whether there is a statistically significant difference in the average length of fixation on products between different age groups (15-18 years, 19-25 years, 26-50 years). The 26-50 age group was excluded from the measurement as this age group had only one representative, which is an unrepresentative sample. Thus, two age groups will be examined, namely the 15-18 age group and the 19-25 age group. To test the hypothesis, we used the statistical method of ANOVA. The following table shows a summary of the basic data before calculating the ANOVA.

Table 2 Basic data for the ANOVA calculation

Groups	15-18	19-25
Number	8	12
Sum	266	414,7142857
Average	33,25	34,55952381
Variance	17,0947522	29,6640383

In this example, the alpha value was 0.05. This means that when the P-value ≤ 0.05, we reject the null hypothesis and accept the alternative hypothesis.

Table 3 ANOVA results

Source of variation	Between Groups	Within Groups	Total
SS	8,23129252	445,967687	454,19898
df	1	18	19
MS	8,231292517	24,77598262	
F	0,3322287		
P-value	0,571487606		
F crit	4,413873419		

Since the F-value (0.3322) is less than F_{crit} (4.4139) and the P-value (0.5715) is greater than 0.05, we do not have enough evidence to reject the null hypothesis. That is, the difference in mean fixation length between the 15-18 and 19-25 age groups is not statistically significant. Based on this analysis, we can conclude that the average length of fixation on products is not statistically significantly different between the 15-18 and 19-25 age groups. Therefore, there is

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insufficient evidence to support the alternative hypothesis that there is a significant difference between these age groups.

Hypothesis 3: Difference in the number of saccades between men and women.

Since the calculation procedure is the same as for Hypothesis 1, we present only the result of the hypothesis evaluation. Since the value of U_{stat}=40 is higher than the critical value of $U_{scritical}$=26, we accept the null hypothesis H0. That is, there is no statistically significant difference in the number of saccades between males and females.

Hypothesis 4: Effect of checkout zone design on product fixation.

To test the hypothesis, we used the statistical method T-test. To calculate the two-sample T-test between two independent samples left checkout zone ĽO7 and right checkout zone PO7, we use the following formula:

$$t = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Where:

- $\overline{X_1}$ and $\overline{X_2}$ are the averages of the two groups (cash zone ĽO7 and cash zone PO7),
- s_1^2 and s_2^2 are the variations of the two groups,
- n_1 and n_2 are the group sizes.

Calculation:

$$t = \frac{42{,}68 - 43{,}87}{\sqrt{\frac{108{,}33}{21} + \frac{157{,}47}{21}}} = \frac{-1{,}19}{\sqrt{5{,}16 + 7{,}50}} = \frac{-1{,}19}{3{,}15} = -0{,}553$$

The p-value is the probability of obtaining such or a more extreme t-value, assuming the null hypothesis (H_0) is true. The t-value, degrees of freedom, and type of t-test (one-sided or two-sided) are used to calculate the p-value for a t-test. The calculation involves several steps:

Determination of T-value and degrees of freedom:

T-value: t=-0.583

We calculate the degrees of freedom df as:

$$df = n_1 + n_2 - 2$$

Where:

- n_1 is the number of observations in the first group,
- n_2 is the number of observations in the second group.

In this case we have $n_1 = 21$ and $n_2 = 21$, so:

$$df = 21 + 21 - 2 = 40$$

We converted the t-value to a P-value using an online calculator available at www.graphpad.com, where we entered values for $t = -0.553$ and for $df = 40$. The result of the calculation, the value is 0.583. This means that the probability that we would obtain this or a more extreme t-value in random sampling, assuming no difference between the means (the null hypothesis is true), is 58.3%. Since the p-value is greater than 0.05, we do not reject the null hypothesis, meaning that there is no statistically significant difference between the groups being compared.

Using statistical methods, Mann-Whitney U test, ANOVA and T-test, we tested four stated hypotheses focusing on different aspects of consumers' visual attention. The results indicated that there were some differences in behaviour between the groups, but not all differences were statistically significant.

Hypothesis 1: Difference in fixation length between men and women.

Accepted hypothesis: (H0) There is no difference in the length of fixation on the product between men and women.

Hypothesis 2: Difference in average fixation by age group

Accepted hypothesis: (H0) There is no difference in average fixation between different age groups (15-18; 19-25).

Hypothesis 3: Difference in the number of saccades between men and women

Accepted hypothesis: (H0) - The number of saccades between men and women is the same.

Hypothesis 4: Effect of checkout zone design on fixation on products

Accepted hypothesis: (H0) - The design of the checkout zone does not affect the length of fixation on products.

Although we hypothesized that there was a difference in fixation duration between males and females, statistical analysis did not confirm this difference. Similarly, when comparing age groups, we did not find significant differences in the average length of fixation on products. On the other hand, experiments with checkout area design provided useful data on how design affects consumers' visual attention, although no statistically significant variation was found.

5. Conclusions

Based on the statistical analysis of the research, it was found that there were no statistically significant differences in consumer behaviour based on gender or age in terms of fixation length and number of saccades. These results may be influenced by the sample size, which highlights the limitations of the study and the need to include a larger sample of respondents in future research. Moreover, differences in checkout area design did not affect respondents' visual attention, suggesting that an effective sales environment does not depend solely on visual design, but also on other factors such as customer movement through the space or pricing.

The research has provided insights into consumer behaviour and their interaction with the retail environment. For retail design professionals, these findings present an opportunity to optimize store elements such as price tags, banner ads and checkout areas to increase customer engagement. Although no significant differences were found between genders and age groups, the data highlight the importance of a clean and visually appealing layout of the sales space and the use of elements that can capture customers' attention.

The findings suggest that future research should focus on a larger sample of respondents and analyse other variables. Exploring other demographic and psychological factors could contribute to a deeper understanding of the complexity of consumer decision-making and the creation of more effective store designs that improve the customer experience and optimize the shopping environment.

Practical recommendations can be formulated in the light of these findings. Visual elements of stores, such as price tags, should be prominent, with legible fonts, contrasting colours and strategically placed at eye level. Advertising banners should be eye-catching, contain concise and clear calls to action, and be placed in high visibility zones. Checkout zones should be minimalist, uncluttered and complemented by impulse products that naturally catch the attention of customers. Technologies such as eye-tracking should be used regularly to analyse the effectiveness of design changes. In this way, it is possible to create store designs that better reflect customer needs and encourage positive buying behaviour.

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