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EVALUATING THE QUALITY AND PROCESS CAPABILITY OF SMARTPHONE NAVIGATION SYSTEMS: A COMPARATIVE STUDY OF TRAVEL TIME PREDICTION PERFORMANCE

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ABSTRACT

The popularity of the use of smartphone-based navigation applications is driven by convenience and the availability of inexpensive mobile data plans. While the main function is routing from one place to another, the second most important function is the estimated travel duration based on the routing provided. From this estimate and the required time of arrival at the destination, a departure time can be planned.

The estimated travel duration needs to be accurate because inaccuracies cause inconvenience at best and lost business opportunities at worst, when arrival gets delayed.

While their popularity could indicate their level of quality, this study presents the real-world performance of 3 of the most widely used navigator applications in their travel duration estimation. Travel parameters are controlled to ensure fairness. Findings indicate capabilities worse than +/-30% error, so travelers need to allow for more time than indicated by these applications.

1. INTRODUCTION

Smartphone technology over the last two decades has changed how we navigate and plan our travel in cities. There are more than 7.2 billion smartphones worldwide, with penetration rates in developed countries reaching roughly 75 percent of the population (market.biz, 2026). In this environment, applications based on smartphones have become an inseparable part of the journey to a desired destination, providing free real-time routing, updating traffic data, and estimates of the duration of travel. This pivot caused a huge change not only in individual travel behaviour but also brought with it major issues over the quality, reliability, and consistency of the information these applications provide.

Metropolitan South Australia - with Adelaide in particular - provides an interesting setting for the investigation of navigation application performance. Adelaide is a car-centric city with 85% of South Australians commuting in private vehicles (South Australian Environment Protection Authority [EPA SA], 2023). Importantly, it is also the only Australian capital where traffic congestion has worsened since 2019 - the number of hours lost to dwell time (this is when a vehicle spends more than one hour traveling at low speed or is stationary) is up 16%, whereas the remaining set of 14 global peer cities has fallen by 27% (Business of Cities 2023; as cited in InDaily, 2023a). In addition, information from the South Australian Department for Infrastructure and Transport (DIT) shows that average travel speed across metropolitan Adelaide has fallen from

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43.5 km/h in 1997–98 to just 35.5 km/h this year - an 18%-drop (InDaily, 2023b). Due to this worsening case of congestion, the need for navigation applications that assist commuters in decision-making on smart routing has become critically important.

2. LITERATURE REVIEW

In the smartphone ecosystem, three navigation applications dominate: Google Maps, Apple Maps and Waze. In the U.S. market, which closely tracks Australian usage, Google Maps holds a 67% share of the overall navigation app market, while Apple Maps has roughly 25% and Waze a shade under 8% (comScore Digital Market Intelligence 2026; as cited in Scrap.io, 2026). In Australia specifically, Google Maps has about 5.7 million active users, while the registered number of Waze's monthly active users was about 967,000 in the second quarter of 2025 (Sensor Tower, 2025). The navigation app sector generated $21 billion in revenue worldwide in 2024, up 14.7% from the previous year; Google Maps accounted for about 59% of that volume (Business of Apps, 2026).

These applications are used every day, but they vary greatly in terms of performance. All three use a different combination of algorithms, data sources and computational methods to produce Estimated Travel Duration (ETD) and Estimated Times of Arrival (ETAs). Anand et al. (2017), for example, showed that navigation applications on iOS, Android and Windows Phone platforms predict travel time without learning individual user movement profiles and have problems with data quality - missing accurate information on location and type of pedestrian crossings or other infrastructure-specific variables. More generally, the algorithms that power contemporary navigation apps combine graph-based routing with machine learning: Google Maps, for example, uses a variant of Dijkstra's shortest-path algorithm called A* (A-Star) which employs heuristic functions to optimise routing efficiency but also incorporates machine learning models from historical traffic data, journey time and anticipated delays (Badola, 2025; Rawat & Kumar, 2025).

Practically, the result of these different methods of computation is that the ETD and ETA for a given route differs significantly across navigation applications even if they were to be calculated simultaneously in the same city environment. Studies conducted primarily in urban environments, however, have demonstrated that while data from access to GPS-based navigation applications such as (Google Maps and Waze) provide real-time traffic information, the fidelity of the ETD and ETA against a known ground-truth remains heterogeneous; trends and anomalies across other navigation platforms also exist (NCUR, 2025). Through the Total Quality Management (TQM) lens, this variability in output is a quality-of-service issue - specifically, the consistency dimension of quality that relates to how consistently a service will produce the same results under similar circumstances (American Society for Quality [ASQ], n.d.).

2.1 Total Quality Management and Digital Service Consistency

Total Quality Management (TQM) is a management philosophy that focuses on achieving long-term success through customer satisfaction and continuous quality improvement - elements of which should be integrated into the day-to-day activities of the organisation (ASQ, n.d.; EBSCO Research, n.d.). TQM started in a manufacturing context, based on the principles of W. Edwards Deming applied to post-war Japan but now it is extended towards services and more recently proposed for digital service organisations. In the digital century, TQM principles like customer-centricity, process management, and continuous improvement can be directly applied to smartphone application assessment (Schiavone et al., 2023).

Applying the concept of service quality to navigation applications is possible through a few dimensions. Of these properties, consistency - the expected reliability of the estimated durations under different conditions and times of day, along a particular route by users with different platforms—is particularly salient. An application doing this across travel durations will erode user trust, hinder decision-making, and may even create larger urban inefficiencies by inducing a more congested or less optimal route selection. It follows that a TQM contextualisation of the comparative study of navigation app ETDs provides a somewhat more coherent and theoretically based context through which these digital services can be evaluated.Key TQM dimensions relevant to navigation app quality:

- Customer focus: Users depend on completing their journeys in time; to achieve that, they rely on accurate ETDs.
- Consistency: ETD and ETA predictions need to be consistent and repeatable, irrespective of the conditions.
- Continuous Improvement: Navigating algorithms must become increasingly more accurate over time.
- Data-driven decision-making: Assessments of route quality should be based on metrics that can be measured and compared.
- Process Management: The algorithmic processes that drive outputs should be responsible and reliable.

2.2 Navigation Algorithms and Estimated Travel Duration

How accurately the travel duration has been estimated will depend, in essence, on the algorithms and data sources different navigation applications use. All major navigation systems are based on a variation of Dijkstra's algorithm (1956) which solves the shortest path problem from a weighted graph corresponding to the road network (Badola, 2025). Google Maps further refines this using A* search, retaining the same basic model, adding in a heuristic cost function to both direct head nodes (the most promising at any iteration) and to prune less likely candidates, cutting down on run time and making it much more viable for real-time navigation over continent scale road networks (Badola, 2025; Besterfield et al., 2011). Using crowdsourced data from active users, dynamic edge weights are tracked in real-time to adjust the traversal time of road segments according to current traffic situations (Rawat & Kumar, 2025).

Apart from graph-based routing, modern navigators utilize machine learning to enhance the approximation of the time it takes to complete a route. It is said that Google Maps trains AI models using historical traffic patterns, peak-hour data, weather conditions, and event information to anticipate when delays will happen before they actually appear in real-time sensor data (Badola, 2025). Chen et al. (2019) presented a two-phase machine learning-assisted navigation-enhancement system consisting of a traffic flow prediction model based on XGBoost coupled with a Top-K Dijkstra algorithm, which showed over 7% improvement when compared to baseline navigation methods in ETD and ETA accuracy. Li et al. A-Dijkstra algorithm: By training on historical GPS taxi data, Zhao (2020) also created an ANN-based model for path planning, whereby the optimal path is given in response to short-term traffic flow predictions.

The main competitive differentiator for Waze is its community-based data model: reports made by real users in real time about accidents, speed traps, road closures, and congestion events are quickly included in the routing. Crowdsourcing makes it possible for Waze to make the hyperlocal traffic information available, which an automated sensor network may falter at. Apple Maps, on the other hand, uses crowdsourced iPhone GPS data processed on-device to produce traffic intelligence, choosing instead to put user privacy front and forward - a design choice that pays some price in regards to real-time coverage but bulks up the system's robustness against malicious attempts at collating individual location profiling from vast amounts of live data (CyberGuy, 2025).

The significance of these varying architectures is that the ETDs and ETAs of each application might exhibit different but somewhat erroneous assumptions about road conditions, past trends, and live occurrences, which leads to very different travel times for comparable journeys. The systematic examination of these differences - particularly in a specific geographical and temporal context such as metropolitan Adelaide - is the main point of this research (Table 1 and Table 2).

Table 1 Smartphone navigation application details. Note. Compiled from: Scrap.io (2026), CyberGuy (2025), Holafly (2026), Business of Apps (2026), Sensor Tower (2025)

Feature	Google maps	Apple maps	Waze
Platform	iOS & Android	iOS only	iOS & Android
Real-time traffic	Yes (extensive)	Yes (crowd-sourced)	Yes (community-driven)
Offline maps	Limited	Limited	No
Data usage	0.67 MB/10 mi	1.33 MB/10 mi	0.23 MB/10 mi
Speed camera alerts	Limited	Limited	Yes (extensive)
Privacy focus	Low	High	Low
Market share (US)	~67%	~25%	~8%

2.3 Smartphone-based Navigation versus Dedicated GPS devices

Before phones were smart, navigating in a car was ruled by stand-alone GPS devices - particularly designed hardware boxes loaded with map software and capable of satellite positioning without any cellular connectivity. These devices provide a number of lasting benefits: they don't use mobile data, they work in fringe or zero cellular signal strength zones, they are purposely designed to have a much longer stand-alone battery life, and the interfaces either started simpler or were easily dumbed down again to beginner level driver expectations suitable for distracted driving (CarBlog, 2025; Cybernews, 2026). One of the significant advantages of using a dedicated GPS device is that it saves on roaming data costs during international travel (CarBlog, 2025).

However, in the modern navigation context, dedicated GPS devices are subject to very tight constraints. Map updates are relatively rare and on most devices must be installed manually, so changes in the local road network may take time to appear. Real-time traffic information is commonly unavailable or very limited and does not allow flexible rerouting if congestion or incidents occur. Dedicated devices are single-use too - just another thing to carry - and generally have very limited map coverage, meaning they really only work in the country you bought them in (makeuseof.com, 2015; CarBlog, 2025).

In contrast, however, smartphone navigation apps are regularly updated in real-time with new maps, incorporate live traffic into route calculations, and work across multiple countries while integrating on a device that users already carry. This comes at the cost of dependence on mobile data connectivity: in network blackspots, smartphone navigation may become poor or totally inaccessible. Another concern, especially for long trips, is the battery drain (Backpacking Guys, n.d.; SectionHiker, 2025). Within metropolitan Adelaide, where cellular coverage is likely strong and users are indeed driving within a well covered networked urban center, smartphone navigation applications emerge as the prevailing and technically superior experience.

Table 2 Comparison between smartphone navigator applications vs. dedicated GPS navigator. Note. compiled from: CarBlog (2025), makeuseof.com (2015), Cybernews (2026), Backpacking Guys (n.d.)

Aspect	Smartphone Apps	Dedicated GPS device
Network dependency	Requires data connection	Works without cellular signal
Map updates	Continous, automatic	Infrequent, manual
Cost	Free	Additional device purchase required
Real-time traffic	Yes – live data	Limited or unavailable
Portability	Multifunctional device	Simple-purpose, extra to carry
International use	Works globally (data needed)	Limited country map availability
Battery life	Drains phone battery	Dedicated, often longer lasting

2.4 Study Context: Metropolitan South Australia

The road network is designed around private vehicle use, and the city is served by major arterial roads, typically radially directed from the City of Adelaide. Only 8.3% of daily trips in Greater Adelaide are made by public transport (EPA SA, 2023), this underlines the impact on road-based travel as commuters rely. Average travel speeds have fallen by 18% since 1997–98 and Adelaide have the unusual distinction among Australian capital cities of traffic congestion getting worse, not measurably better (InDaily, 2023a; InDaily, 2023b). Among the major contributors identified, is an increase in light commercial vehicles, up 40% nationally over the past 10 years (InDaily, 2023b).

Such a setting makes it all the more important that ETDs and ETAs shown on navigation applications are accurate. Commuters who utilize smartphone navigation applications to aid real-time route guidance in a congested and chronically delayed city where disruptions cause highly variable ETD and ETA inaccuracy. If an application always underestimates travel times, users may fail to plan time accordingly, and if it overstates the duration, people risk losing time on unnecessary detours. It is therefore of immediate practical importance to individual commuters and urban transport planners in South Australia to understand which applications tend to perform best—and where they diverge most.

2.5 Research Scope and Objectives

Google Maps, Apple Maps and Waze - about agreement between estimated travel durations across metropolitan South Australia. Based on the principles of Total Quality Management (TQM): consistency, customer perspective, and data-and-information driven assessment, this research aims to:

- Compare the ETD predictions of Google Maps, Apple Maps, and Waze for equal routes in metropolitan Adelaide.
- Evaluate how variable the ETD across varying times of day, route types, and traffic situations.
- Discuss the advantages and disadvantages of the algorithmic approach used by each of the applications being considered in terms of metropolitan road conditions encountered in South Australia.
- Provide a more empirical basis to guide navigation app users and urban transport actors on the choice of an application and whether it can be trusted.

3. METHODOLOGY

For evaluating the accuracy, consistency, reliability, and process capability of the Estimated Travel Duration (ETD) and Estimated Time of Arrival (ETA) predictions, this study used quantitative and comparative research. The comparative research of the study was to evaluate the three smartphone navigation applications—Google Maps, Waze, and Apple Maps—regarding their accuracy, consistency, reliability, and process capability of the ETD predictions. The quantitative research done is to measure performance differences, analyse variance, and statistically support patterns within the data collected, taking an objective approach (Creswell & Creswell, 2018). The favored method was the comparative approach since the key aim of the study was to evaluate and contrast the success rates of ETD prediction across various navigation platforms in similar conditions.

This research is based upon Total Quality Management (TQM), where the focus is on customer satisfaction, continuous improvement, process consistency, and minimising variations where possible (Evans & Lindsay, 2020). TQM takes the concept of quality beyond the average performance; it also considers whether a process behaves in a consistent or reliable way to a customer's expectations. Thus, not only prediction accuracy, but also process variation, stability, and capability were studied. To assess the capability of each ETD prediction system to meet the specified performance requirements, it was decided to use the Statistical Process Control (SPC) techniques and process capability indices (Montgomery, 2020).

The quantitative method was deemed suitable as it allows for the numeric measurement of the performance of the ETD to be measured by the estimated and actual travel time. The collected data allowed the calculation of prediction errors, percentage errors, Mean Absolute Error (MAE), Standard Deviation (SD), Variance, and Process Capability Indices. These measures included objective indicators of navigation system performance and helped provide evidence-based comparison across applications. In addition, inferential statistical analysis was performed using the Wilcoxon signed-rank test to investigate if any significant results between the traffic condition and navigation application were found.

3.1 Study Setting

This study took place in the real-world driving environment, within the metropolitan areas of South Australia. Real world testing was used to enable the same environment and traffic conditions found on the road to be used for the evaluation of the navigation applications. Real world data enables an ETD and ETA prediction algorithm to adapt to the changes in traffic conditions, road congestion, signal delay, route changes, and other environmental factors that affect the time it takes for trips to complete, in contrast to the results of a simulation-based study (Hyndman & Athanasopoulos, 2021).

Two different traffic conditions were evaluated to record the differences in traffic conditions for data collection. The first observation period was on a Tuesday evening and was typical weekday conditions with some commuter traffic and higher volume of traffic and travel-time variability. The second observation period was on a Saturday morning and was for weekend traffic, which tends to be less congested and have a more consistent traffic flow. Having both day and night observations allowed for analysis of navigation application performance under different traffic situations and of the reliability of ETD prediction systems.

Google Maps, Waze, and Apple Maps were used to assess each journey, with a total of thirty navigation observations made. The distances traveled varied from about 12 km to 15 km depending on the route chosen by the different navigation apps. In reality, it took between 19-36 minutes to get to school. The travels were chosen to cover some typical situations in urban travel, and they represented a wide range, for comparison of the performance of ETD prediction.

3.2 Data Collection Environment

All the measurements were based on a standardised procedure throughout the study to enhance the findings' validity and reliability. The same origin and destinations were used for each journey to test all navigation applications. Since the traffic has often changed, the vehicles would leave within about 1-2 minutes to reduce the impact of these quickly changing traffic conditions. These measures made it possible to ensure that the same environmental conditions were experienced by all the navigation applications during the time of the observations and minimized the possibility of poor performance being due to factors other than the performance of the application-specific prediction algorithm.

The different navigation apps were allowed to select their own routes since this is part of the ETD prediction process to be evaluated. Detailed directions were given for driver use of the recommended routes, with an emphasis on observing road safety and traffic laws. Drivers were asked to adhere to directions with accuracy but with the requirement to comply with road safety and traffic regulations. Navigation applications were alternated among the drivers on various trips to reduce possible bias created by driving habits. This has helped minimise the effect of driver variables and ensured a more consistent set of observations.

The following structured method was used to document the data from the screenshots. A capture of the screenshots of each navigation application was made before departure to record the Estimated Time of Arrival (ETA), Estimated Travel Duration (ETD) and estimated travel distance. When arriving at the destination, further screenshots were taken to document the Actual Travel Duration (ATD) and Actual Time of Arrival (ATA). Recorded information was then typed onto a structured spreadsheet for analysis. This was an effective way of keeping a proper record of observations and minimizing the risk of observer or transcription errors. This data was used for descriptive statistical analysis, graphical process analysis, hypothesis testing, and process capability assessment.

Constructing a controlled and consistent data collection environment helped to achieve the increased reliability of the study and guarantees comparisons between the different navigation applications were being made in terms of differences in ETD prediction performance, and not inconsistencies in the data collection process. The standardisation has been introduced in line with TQM project ideas where emphasis is placed on process control, the quality of the measure passed, and minimizing unwanted variation. A prerequisite for meaningful evaluation of quality is to have a project where process control is established, the measurement is accurate, and/or unwanted variation is minimized (Evans & Lindsay, 2020; Montgomery, 2020).

3.3 Participants and Journey Selection

The study was done by the project group members who volunteered to drive and participate in data collection activity. Responsibilities of each participant throughout the study varied, with some doing driving, some navigation monitoring, others observations, and still others data recording. Multiple participants allowed for the simultaneous testing of navigation applications, and increased accuracy and reliability of collected observations. Multiple observers are often used in some case studies when using the quantitative method because this is to reduce the number of errors and to help verify the data when conducting field-based studies (Creswell & Creswell, 2018).

The selected journeys for this research traveled through several destinations within metropolitan Adelaide, South Australia, with the intention that navigation applications would be tested in realistic metropolitan driving conditions. This series of journeys is specified in Table 3, which is based on the average working person's commute of 13.5 km in Greater Adelaide as reported by the Australian Bureau of Statistics (2018). This approach created a series of linked journeys: each destination was the starting point for the following journey. The series of journeys traveled through a mixture of urban road types: residential roads, arterial road corridors, signalised intersections, shopping districts, and variable road traffic. These road types are assumed to provide a suitable testbed in that they ensure that the navigation applications encountered typical urban traffic, were challenged by complex roads, and faced various travel-time effects. The journey series traveled between the western region of Adelaide and an eastern region. Maintaining constant origin and destination between the journeys ensured that journey complexity, and traffic characteristics faced were maintained across all navigation applications when assessing ETD accuracy, reliability, and the process variability of each of Google Maps, Waze and Apple Maps. Travel-time prediction studies have noted the need to consider realistic navigation scenarios when evaluating the performance of travel-time prediction systems since travel behaviour and traffic variability are significant factors in this performance (Vlahogianni et al., 2014).

Table 3 Start/end location of the trips

Address ID	Location
Address 1	Aberdeen Street, Port Adelaide SA
Address 2	Hurcombe Street, West Beach SA
Address 3	George Street, Unley Park SA
Address 4	Savas Road, Rostrevor SA
Address 5	Forster Street, Ridleyton SA
Address 6	Cornell Avenue, Valley View SA

Altogether, thirty trips were made in the study. Six navigation observations were recorded for each journey, using Google Maps, Waze, and Apple Maps. The average travel distance was about 12 km to about 15 km based on the route chosen by each application, and the actual travel time ranged between about 19 - 36 minutes. Repeat observations on several journeys were needed to analyse the variation and consistency of processes, not just a single observation! Many observations are required in a TQM system, as process performance needs to be assessed over time to see if there are patterns of variation, and to establish reliability (Evans & Lindsay, 2020).

Collecting the journeys under two contrasting traffic conditions: Tuesday evening to capture daytime commuter traffic, and then Saturday morning to capture lighter weekend traffic conditions. This comparison allowed an investigation to be conducted on whether the performance of the ETA is stable under varying traffic conditions. When performing evaluation under different operating conditions, it becomes evident that the process of assessing performance under multiple operating conditions is consistent with the quality management paradigm, which places an emphasis on understanding process behavior under different environmental influences (Oakland, 2014).

3.4 Standardised Driving and Data Collection Procedures

A standardised driving procedure was adopted for the entire study to make the navigation applications as easy as possible to compare and limit any other unnecessary variations. Standardisation is one of the core elements of quality management and is crucial in ensuring consistency in measurement and the ability to control external variables that may influence the performance of the process (Montgomery, 2020). The research was designed to hold testing conditions constant so that the differences in ETD prediction performance that were found could not be blamed on differences in how the data was collected.

All the navigation applications were tested with the same sources and destinations for each trip. Cars started off within about 1–2 minutes of each other to reduce differences due to variation in traffic conditions. Three vehicles were operated at the same time using various navigation applications and were thus subject to similar traffic conditions and road network conditions. This way it minimised the effect of variations in traffic volumes from one time to another and made it easier to compare the results of the ETA predictions.

A test component for the route selection was included in each navigation application, which was free to independently choose their route. Limiting routes might not represent application performance and diminish the ecological validity of the study. Drivers were asked to stick to the recommended routes as far as practicable, but to ensure that traffic regulations and safety aspects were adhered to. Any deviation not caused, and deemed unavoidable, by road, traffic, or safety conditions was counted as part of normal driving.

Another tactic used to eliminate bias was to rotate navigation applications between drivers during the study. This procedure minimized subject variations due to the familiarity with the routes, drivers' behaviors, and decision making. Across the observations, the same vehicles were used to reduce variability in the effects of the characteristics of the vehicle. Attempts to eliminate unwanted variation with such attempts are aligned with Six Sigma and TQM approaches, prioritising process control and lessening contributing variation-causing factors (Pyzdek & Keller, 2014).

A standard driving procedure ensured the reliability and validity of the acquired observations and thereby assisted in satisfying the goal of evaluating ETA prediction systems from a process quality perspective. Past research on the same topic has identified how important the operational conditions are when comparing travel-time prediction technologies (Vlahogianni et al., 2014).

The data was collected by a structured method of screen-based recording to ensure consistency, traceability, and accuracy of observations. One of the key steps in a quality management system is to measure things accurately, because analysis of processes is fundamental to quality management and requires reliable and valid data (Montgomery, 2020). Accordingly, the procedure was taken to take ETA predictions and actual travel results during the study in a systematic way.

Before the start of every trip, the designated navigation app was turned on, and a screenshot was taken immediately before the start of the trip. This screenshot recorded the ETA, ETD, and estimated travel distance provided by the app. According to the navigation system, these estimates represented the expected travel time based on the algorithms of the navigation system, historical traffic data, and real-time traffic conditions. Due to accurate prediction assisting users of intelligent transport system in route planning and scheduling decision making the travel-time estimation is critical (Vlahogianni et al., 2014).

A second screenshot was taken upon arrival, right after the navigation app said that “You have arrived at your destination.” This screenshot shows the actual time of arrival and actual travel duration. Using a screenshot cuts down on the risk of manual timing errors and establishes a permanent record of observations that can be independently verified, if needed. The data collected were later entered into a structured spreadsheet created for the research.

The data collection table contained trip identification number, navigational application, date, day of the week, name of the observer, travel commencement time, estimated travel distance, ETA, ETD, ATA, and ATD. The spreadsheet calculated various more performance indicators, including ETA prediction error, percentage error, MAE, standard deviation, variance, and process capability measures automatically. MAE was chosen as it is an easy-to-interpret measure of average prediction accuracy and a commonly used measure in forecasting and prediction studies (Hyndman & Athanasopoulos, 2021).

Each observer followed a standardised recording procedure to enhance the quality of data. From a TQM perspective, it is important to have reliable measurement systems because process improvement initiatives are based on reliable assessment of performance and variation. The resulting dataset was used for descriptive statistics analysis, graphical quality analysis, nonparametric hypothesis testing, and process capability assessment.

3.5 Research Variables

The independent variable in this study was the smartphone navigation app used to estimate travel time. The three apps chosen for comparison were Google Maps, Waze, and Apple Maps. These apps were selected because they are popular among smartphone users and provide real-time Estimated Travel Arrival (ETA) and travel duration (ETD) information. Using multiple apps allowed the study to compare prediction performance across different navigation platforms under similar driving conditions.

The dependent variables measured in the study were ETD prediction error, percentage error, Mean Absolute Error (MAE), standard deviation, variance, and process consistency. These variables were chosen because they assess both prediction accuracy and reliability. From a Total Quality Management (TQM) perspective, service quality is not only about whether an app can give a close estimate on one trip, but also about whether it can reliably provide consistent estimates across multiple trips. Therefore, both the size of the error and its variation were seen as important indicators of quality performance (Evans & Lindsay, 2020; Montgomery, 2020).

ETD prediction error was used to determine if the application's prediction was below the actual travel time, or not. Percent error was utilized to measure the ETD prediction error as a percent relative to the trip length to enable comparison between trips of varying lengths. MAE was used to represent the average size of the prediction error regardless of whether the predicted travel time was higher than or lower than the actual trip length. The standard deviation and variance were calculated to assess the variability in prediction performance. Quality management aims for lower variability, which suggests more consistent, reliable processes (Montgomery, 2020), therefore, lower error and variability in an application predicted that the application's quality of prediction was superior.

3.6 Calculations

ETD error was derived by subtracting the Estimated Travel Duration (ETD) from the navigation application from the Actual Travel Duration (ATD) collected at the end of each trip. The following formula was utilized:

$$ETD\ Error\ = ATD - ETD$$

In this study, a positive ETD error value signifies an underestimation of travel time. This means the navigation application was not accurate, and the actual trip took longer than was predicted by the application. Conversely, a negative ETD error signifies an overestimation of travel time. This means the navigation application was also not accurate, and the actual trip took less time to complete than was predicted by the application. It is important to note that underestimation has a potentially stronger negative impact on a user, as late arrival could make them late and less confident in the navigation application.

Percent error was then calculated as a measure to compare ETD prediction error to the overall trip length:

$$\%\ Error = \frac{ETD\ Error}{ATD} \times 100\%$$

This calculation enabled errors from trips of varying lengths to be compared more equally.

Mean Absolute Error was used to measure the magnitude of prediction errors regardless of under- or overestimation. It is often useful to employ MAE for accuracy measurements in forecasting and prediction analyses, as it is a simple, easily interpretable statistic representing the average accuracy of prediction (Hyndman & Athanasopoulos, 2021).

$$MAE = \frac{Sum\ of\ absolute\ ETD\ errors}{Number\ of\ observations}$$

These calculations provided the building blocks to assess ETA prediction quality between each application and each specific traffic condition. They also allow us to compare the mean, magnitude, direction of error as well as variability, all of which are important components of a quality management analysis.

3.7 Descriptive and Graphical Statistical Analysis

Descriptive statistical analysis was carried out to compare and summarize the ETD prediction performance across Google Maps, Waze, and Apple Maps. Key descriptive statistics were the mean error, Mean Absolute Error, variance, and standard deviation. These were utilized to allow for a comprehensive overview of the accuracy and variability of the ETD.

The mean error was utilized to establish the overall trend of bias in the prediction (whether over- or under-estimation). A negative mean error implies that an application predicted that travel would take longer than reality (overestimation); a positive mean error implies that it predicted that travel would take less time than reality (underestimation). A drawback of solely looking at mean error, is that positive and negative errors can counteract each other, so MAE was also computed to better summarize average prediction error. Standard deviation and variance are utilized to see the consistency of the ETA prediction. A small standard deviation signifies a high level of consistency; this means that prediction errors were very close to the mean, thus it was consistently not over- or underestimating the ETD. As variation is something the study is trying to reduce, standard deviation and variance are key values.

The descriptive statistics were computed individually for each application and by the day type. This analysis aimed to highlight how the accuracy and variance of the prediction changed from a typical Tuesday evening traffic condition to a Saturday morning leisurely trip. As the sample size is minimal, caution had to be taken with drawing conclusions; therefore, the analysis was combined with the graphical analysis and a non-parametric Wilcoxon signed-rank test, with the process capability analysis to give a full picture.

Graphical analysis was applied to help determine the accuracy, variation, distribution, and stability of prediction errors for ETD provided by Google Maps, Waze, and Apple Maps. Graphical quality tools are frequently utilized within the quality management arena since they serve as instruments for pattern recognition, detection of trends, variation, and unexpected or anomalous occurrences that are likely to remain hidden in quantitative evaluation (Montgomery, 2020). In addition, visual analysis assists in the monitoring and behavioral description of processes, which is one of the aims of Total Quality Management and continuous improvement (Evans & Lindsay, 2020).

Various techniques for graphically displaying data are utilized herein; scatter plots, box plots, histograms, Statistical Process Control (SPC) charts, and Moving Range (x-MR) chart plots are among these. In a Scatter plot, visual examination was used to determine how close the prediction results were to actual travel results. Higher precision in estimation implies that the points are near the line of equal prediction. Box plots were applied to display the percentage error distribution of each of the three navigation applications. Smaller variance indicates the stability of the prediction. Histograms were used to demonstrate the distribution shape for the percentage errors and to investigate the rate of over- and under-prediction.

Control charts and Moving Range charts were created to monitor process variability and stability over time. SPC methods are commonly used in quality management to distinguish common and special cause variability, and to determine if a process is running in a stable and predictable pattern (Montgomery, 2020). X charts were utilized in the process of analyzing the percentage errors of consecutive trips, whereas Moving Range charts measured the variation between successive measurements. Processes that exhibit a more consistent output, or that stay within predicted control limits, are thought to be of more consistent quality.

3.8 Inferential Statistical Analysis

To confirm whether the disparities found between traffic conditions, and navigation applications regarding their prediction performance were statistically significant, an inferential statistical analysis was performed. Statistical tests in quantitative studies play an important role, where such tests are used to evaluate whether observed variations between different research groups are likely to stem from variations in performance or from pure random chance (Creswell & Creswell, 2018).

Given that there was a small sample size, and that the assumption of normality could not be safely guaranteed, the Wilcoxon signed-rank test was chosen to perform inferential statistics tests. The Wilcoxon signed-rank test is a non-parametric substitute for the paired-samples t-test, which is applicable for paired data sets that might violate the assumption of normality (Field, 2018; Gibbons & Chakraborti, 2020). Non-parametric analyses are considered more suitable for smaller data sets because they utilise rankings of data rather than relying on distributional assumptions.

The Wilcoxon signed-rank test was used to calculate whether there was a statistical difference between weekday and weekend percentage errors within each navigation application. In addition, each navigation application was compared against the other two navigation applications to determine if any significant differences in prediction accuracy existed between Google Maps, Waze and Apple Maps. For each of these tests, the null hypothesis (H0) was that there was no significant difference between percentage error pairs, whereas the alternative hypothesis (Ha) was that there was a significant difference between the pairs.

A confidence level of 95%, corresponding to a significance level of 0.05, was set for significance testing. A P value of less than 0.05 was used as evidence against the null hypothesis, meaning that a statistically significant difference was demonstrated between observations and that the null hypothesis was rejected, and the alternative hypothesis accepted. Conversely, when a p-value of more than 0.05 was calculated, there was not sufficient evidence to reject the null hypothesis and conclude that there was a statistical difference between groups, which is compliant with TQM principles of evidence-based decision-making (Evans & Lindsay, 2020).

3.9 Process Capability Analysis

A process capability analysis was performed on the ETD prediction processes to measure the ability of these processes to consistently produce outcomes within the specified customer limits. Within Total Quality Management (TQM) and Six Sigma practices, process capability is one of the key quality measures because it indicates how well a process is performing about the limits set by the customer (Montgomery, 2020; Pyzdek & Keller, 2014). A capable process is one that has very little variation and is centered properly between the specified limits to ensure the customers' requirements are met consistently over time.

The process capability was determined for the processes in this study using Cp and Cpk indices. The Cp index is an index that is used to assess the potential capability of the process by relating the variation in the process to the specification limits, whereas Cpk considers both the variation and centering relative to the closer specification limit (Montgomery, 2020). High values for Cp and Cpk signify good process capability and a high ability for the process to meet the specified customer requirements. In quality management, this type of analysis is most commonly used within Six Sigma projects because the results of the analysis directly report the process's ability to satisfy customer requirements regularly (Besterfield et al., 2011).

For this study, the customer specification limit was set at +/-10% error in ETD prediction to represent the desired quality level as a reasonable user-defined requirement for prediction accuracy. The percentage error values were chosen as the capability characteristic because they represent the prediction errors relative to Actual Travel Duration, allowing the results to be standardized across a wide range of journey lengths and be comparable. Cp and Cpk values were computed separately for Google Maps, Waze, and Apple Maps from the observed percentage error data sets.

Unlike other statistical measures that report on the central tendencies of a data set, the process capability measure indicates whether the customer will receive the predicted level of quality on a consistent basis. In quality management, customers ultimately define quality as receiving consistently repeatable performance and not just an occasional accurate measurement (Evans & Lindsay, 2020). Process capability analysis complements traditional descriptive and inferential statistics by illustrating the consistency of the ETD and ETA prediction performance of each application over a long period of time.

4. RESULTS

4.1 Analysis of ETD Error Trends

ETD error charts for Waze, Apple Maps and Google Maps are shown in Figure 1, Figure 2 and Figure 3. The %Errors varied from the ten journeys performed for each application. The errors were positive and negative with mean error for Waze being -0.85%, for Apple Maps being 10.88% and for Google Maps being 6.17%. The majority were within the derived control limits.

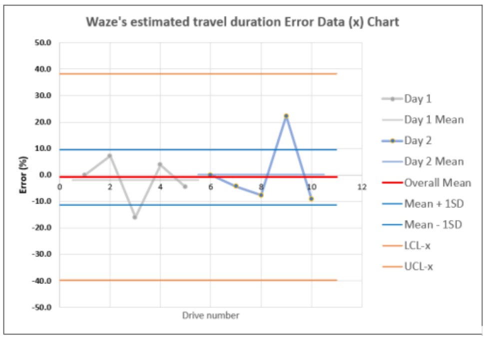

Figure 1. Estimated Travel Duration Error Data Chart for Waze

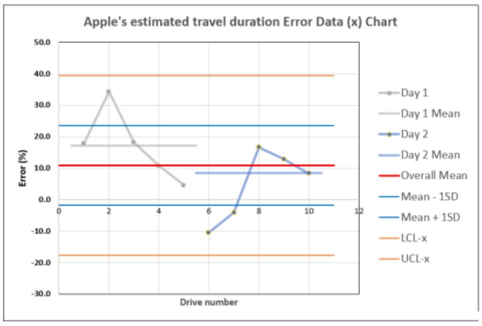

Figure 2. Estimated Travel Duration Error Data Chart for Apple

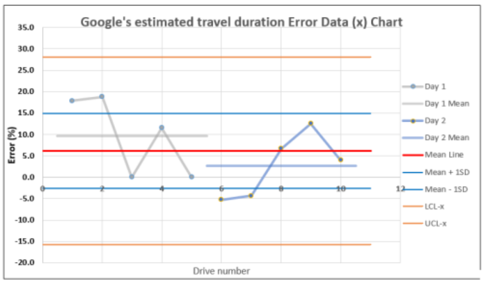

Figure 3. Estimated Travel Duration Error Data Chart for Google

4.2 Boxplot Analysis

Boxplots of percentage prediction error for the three navigation apps are shown in Figure 4, Figure 5, Figure 6. The boxplots show variability in error distributions and differences in variations between navigation apps. Apple Maps shows the largest span in errors. Both Waze and

Google Maps seem to have smaller ranges in error variations.

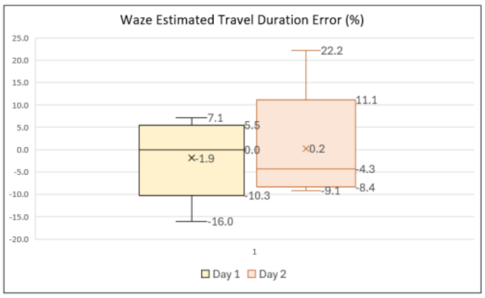

Figure 4. Boxplot Analysis of error for Waze

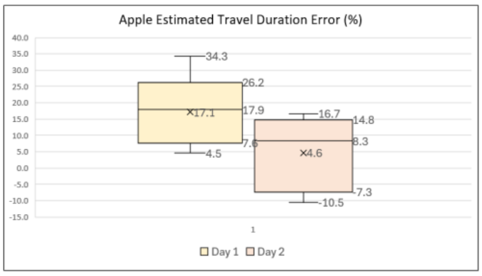

Figure 5. Boxplot Analysis of error for Apple

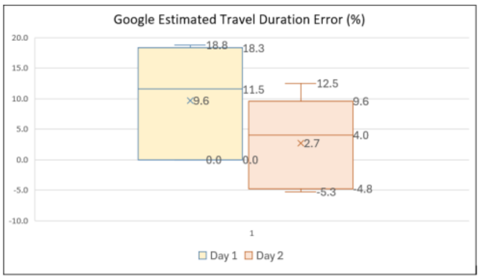

Figure 6. Boxplot Analysis of error for Google

4.3 Histogram Analysis

Histograms were created to understand the distribution of ETD errors. For all 3 applications, the prediction error seems to be centered on the mean. However, in terms of the dispersion of the observations, the applications differ from each other. In Apple Maps, the distribution of errors is wider than in Waze and Google Maps. See Figure 7, Figure 8, and Figure 9.

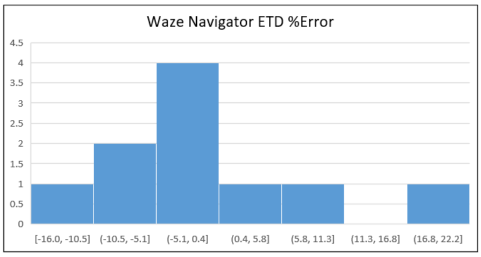

Figure 7. Histogram of Waze Estimated Travel Duration Error

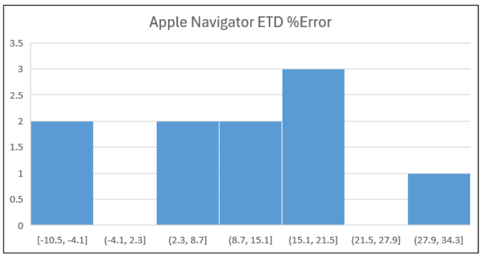

Figure 8. Histogram of Apple Estimated Travel Duration Error

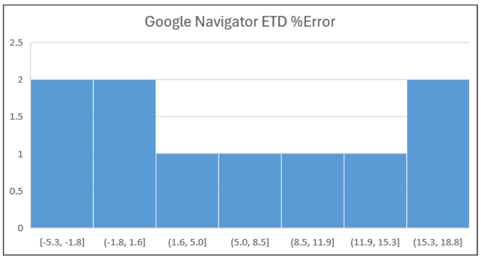

Figure 9. Histogram of Google Estimated Travel Duration Error

4.4 Statistical Process Control (SPC) Charts

The SPC charts were introduced to check the stability of the process. All three navigation applications have percentage errors within calculated UCL and LCL limits. No point falls outside control limits. See Figure 10, Figure 11, and Figure 12.

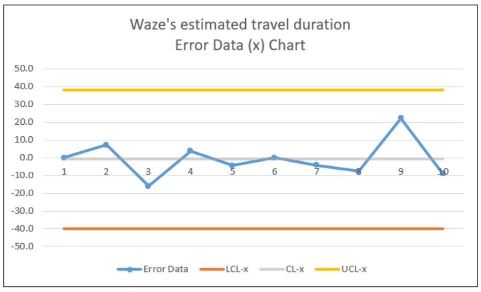

Figure 10. SPC x-Chart for Waze

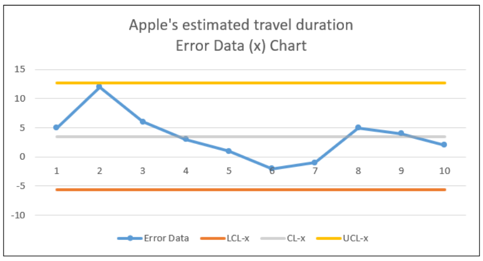

Figure 11. SPC x-Chart for Apple

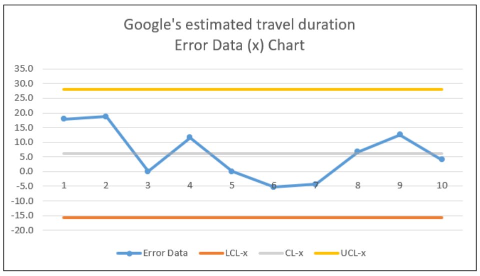

Figure 12. SPC x-Chart for Google

Moving range charts were employed for the analysis of variability between successive values. They show that the estimation error of ETD varies from one trip to the next, and all the values fall inside the control limits that have been computed. Larger values were obtained by Apple Maps compared to Waze and Google Maps. See Figure 13, Figure 14 and Figure 15.

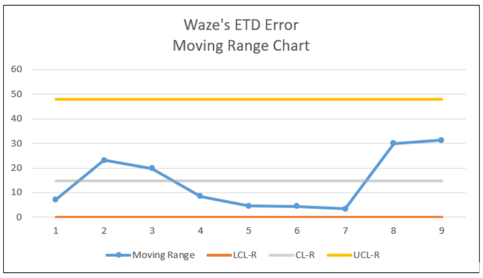

Figure 13. Moving Range Chart for Waze

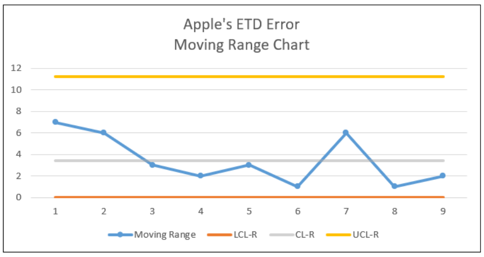

Figure 14. Moving Range Chart for Apple

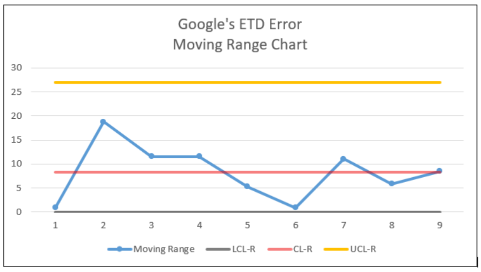

Figure 15. Moving Range Chart for Google

4.5 Comparative Error Analysis

In Figure 16 and 17, we plot predicted ETD error and error fluctuations across Waze, Apple Maps, and Google Maps. We can observe the discrepancy in the size of error values and variations across each application during the course of the ten trips. We notice that the percentage errors in Apple Maps tend to be much greater, while Waze and Google Maps exhibit relatively lower error values.

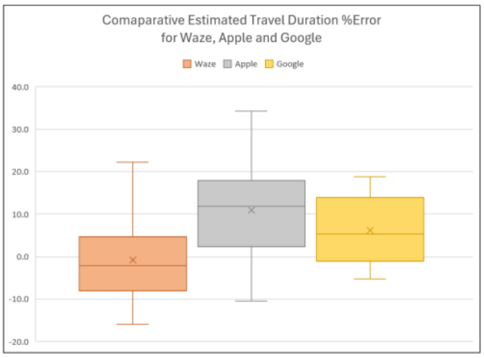

Figure 16. Comparative ETD Errors

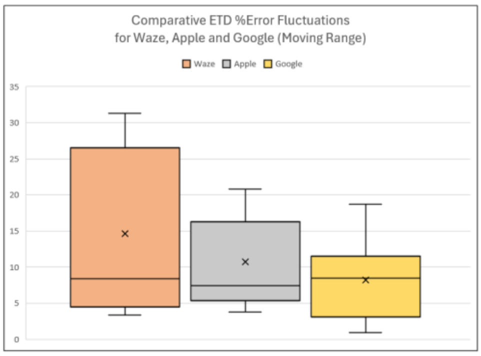

Figure 17. Comparative ETD Error Fluctuations for All Three Apps

4.6 Process Capability Analysis

Process capability analysis was performed using the Cp and Cpk indices for a prediction error customer spec limit of +/-10%. All the navigation applications were not capable of the given specification. Waze and Google Maps were capable at +/-32.5% error, while Apple Maps was capable aat +/-49% error.

4.7 Hypothesis Tests

To identify if there were any significant differences between weekend and weekday prediction error percentage, Wilcoxon signed-rank test was run on the dataset of Waze, Apple Maps, Google Maps, and a combination of the three. The null hypothesis was that there is no difference in weekday vs. weekend percentage prediction errors, and the alternative hypothesis was that there is a difference in weekday vs. weekend percentage prediction errors. See Table 4. None of these p-values are less than the level of significance, = 0.05; the null hypothesis was not rejected, and there was no significant difference between weekend and weekday ETD prediction errors.

Table 4. Wilcoxon Signed-Rank Test Results: Comparing Weekdays vs. Weekends

Comparison	p-value	Decision
Waze vs Apple Maps	0.0666	Fail to reject H_0
Google Maps vs Apple Maps	0.1235	Fail to reject H_0
Waze vs Google Maps	0.0580	Fail to reject H_0

The Wilcoxon signed-rank tests were also performed on the prediction errors between navigation applications. See Table 5. Each of these was larger than the desired alpha of 0.05, so none of the comparisons' null hypotheses were rejected. There was no statistically significant difference in ETD prediction error between the navigation applications.

Table 5. Wilcoxon Signed-Rank Test: Comparison of Navigation Applications

Comparison	p-value	Decision
Waze vs Apple Maps	0.0666	Fail to reject H_0
Google Maps vs Apple Maps	0.1235	Fail to reject H_0
Waze vs Google Maps	0.0580	Fail to reject H_0

5. DISCUSSION

5.1 Interpretation and Analysis of Results

The statistical analysis showed distinct differences in travel time prediction accuracy between the three navigation systems (Waze, Apple Maps, and Google Maps) for the percentage error measure. Waze had the lowest variation overall and was the most consistent of the three applications in the accuracy of predictions. None of the three applications, however, could achieve the desired specification limits of ±10% error.

The process capability analysis of the resulting percentage error estimates indicated that the process is in control, and the natural process tolerances are approximately ±32.5% for Waze, ±49% for Apple Maps, and ±32.5% for Google Maps. All three of the navigation applications showed prediction variability outside the acceptable specification range, which means that the processes are not currently statistically capable of meeting the required accuracy standard.

The graphs indicate that overall, Waze had the lowest average percentage error, while Google Maps had the least variation in the percentage error between the routes and travel days. The percentage error values ranged the widest and were highest in Apple Maps, particularly if the travel time was recorded during the day. Google Maps has relatively low but consistent performance throughout the time series. All applications were also found to perform more consistently during the Saturday travel days compared to the Tuesday travel days from the day-based analysis. This may indicate that there are fewer changes in traffic congestion on weekend trips.

The route-dependent charts also indicate that there are differences in the stability of route prediction accuracy for the various routes on each platform, with some routes being stable in terms of prediction accuracy on some platforms but not others. The hypothesis testing results did not fully support these observations statistically, although there appeared to be differences between the applications in the graphical analysis.

The hypothesis test results indicated that the differences in the mean percentage error were not statistically significant at the chosen confidence level. In other words, the charts seem to prove Waze to be more successful, while the statistics suggest not enough data has been collected to definitively confirm that there is a significant difference between the accuracy at which the two applications predict the traffic. The lack of statistical significance could be due to the relatively small sample size, the number of routes, and/or the limited travel periods. Further standardised experiments over a longer period and under a wider range of traffic conditions would enable more reliable conclusions and give more statistical certainty of the differences seen when comparing the performance of the navigation applications.

The results in terms of Total Quality Management (TQM) very much link to customer focus, which outlines that customers expect accurate predictions of arrival times, consistent navigation performance, and reliable routing (Goetsch & Davis, 2016).

Customer satisfaction and trust can be achieved better with applications that consistently deliver reliably accurate travel time estimates. The results also show the spirit of TQM, which is to continually improve. Navigation systems (Oakland, 2014) are vital and rely on the ability to process data in real-time, ability to predict traffic, and continuous optimisation of data. Waze's superior visual capabilities might be a way to improve traffic control more dynamically and continually enhance the system.

5.2 Comparison with Existing Literature

The results of this study are mostly consistent with the previous studies on the performance of navigation applications. Waze is widely recognized in the literature as being very effective when it comes to real-time traffic management, as it has a crowd-sourced reporting system, and provides dynamic route optimisation (Bar Hillel et al., 2015).

Google Maps is often known for its user-friendly performance and comprehensive mapping capabilities, whereas Apple Maps has a history of varying travel time estimation precision (Zhao, 2020). The present study corroborates these observations graphically, specifically about the smaller mean variance of Waze and the larger percentage error range distribution of Apple Maps.

Previous studies also have pointed out that the accuracy of navigation can be different when traffic is heavy, the geographical environment is different, it is daytime, or the driver's actions are different (Wang et al., 2019; Werner & Zeitz, 2022). In the same way, greater variability for the weekday travel conditions was found in this study compared to the weekend travel conditions. The visual trends detected in the charts, however, were not supported by the statistical hypothesis tests, which did not show any significant difference between the applications at the selected level of confidence. This means that further data collection and subsequent standardised testing may be needed to statistically support the performance differences found.

5.3 Limitations of the Study

There are a few limitations in interpreting the results of this study. First, the sample was small and confined to the number of routes and travel days. The findings would be more reliable and have greater statistical power and generalisability if the amount of data were collected over an extended period (Goetsch & Davis, 2016).

Secondly, the study took place in a specific geographic region, so the results may not be applicable to all cities, regions, and countries with varying traffic systems and infrastructure. Also, data collection was designed to minimize but not fully control the effects of external factors, including weather, roadworks, accidents, and driver actions and behaviours. The actual time spent traveling may have been affected by these factors and contributed to the differences in percentage prediction error between the applications (Oakland, 2014).

A drawback is that the study did not consider other factors of customer satisfaction; that is, user interface quality, route safety, ease of use, fuel efficiency, etc.

Finally, the hypothesis testing results did not provide conclusive statistical evidence that there were performance differences between the applications as suggested by the charts. The future use of larger datasets in further standardised experiments would strengthen future statistical analysis and process capability evaluation.

6. CONCLUSION

Results suggest that all three navigation systems could reasonably estimate travel times but that there were discernible variations and consistency in their ETD estimates. Waze had the lowest average percentage error and showed less variability between trips and traffic conditions of the three applications. Google Maps also had comparatively lower variability in its results and relatively stable performance, whereas Apple Maps had relatively greater fluctuations and higher prediction ranges, especially during high traffic or city conditions.

The navigation applications, in general, were within statistical control, but none of the applications met the desired specification limits of ±10% prediction error. The natural process tolerance limits were significantly larger than the desired range, which suggests that the prediction systems are not yet statistically capable of consistently achieving the required performance. The results confirm the need for variation reduction and process improvement in the technology of navigation, especially in the changing traffic situation.

Additionally, the study revealed that the traffic density, road type, and time of day were among the external operational parameters that had a significant impact on the accuracy of ETD prediction. The weekend travel periods most often resulted in more consistent and stable predictions, which indicated that the traffic pattern variations were still a significant factor in the variation of the process.

In light of the TQM point of view, this research indicates that the application of both quality management principles and statistical process analysis principles to the digital navigation system is valuable. The study tested the stability and performance consistency of the navigation applications using benchmarking, process capability analysis, x-MR control charts, standard deviation, and percentage error evaluation. These tools allowed for an in-depth understanding and assessment of process variation and service reliability and led to the realization that navigation applications can be seen as quality-driven service systems where customer satisfaction is greatly dependent on accuracy, consistency, and service improvement.

The findings also complement the literature as they expand the field of application of the TQM principles to the field of smartphone navigation technologies. This research not only identifies the significance of process stability and quality measurement but also emphasises the significance of customer-oriented performance evaluation in digital transportation services, areas that have been overlooked by previous studies.

Despite the findings that were of value, there are also limitations in the study. The sample size and observation period were relatively small, and the data collection was limited to selected metropolitan routes in South Australia. Random external factors like temporary road and traffic incidents, roadworks, weather conditions, and driver response behaviour could have impacted some travel outcomes. Random variation was reduced by taking an average of multiple observations, but additional observations on larger datasets, more routes, longer observation periods, and more driving environments would yield greater statistical confidence and provide greater power to the process capability assessment.

Advanced TQM techniques, such as more detailed analyses of control charts, better process capability analyses in real time, and more detailed error classification approaches, could also be expanded to assist in continuous improvement of the quality of navigation systems in the future.

In general, the quality of the ETD prediction differs in various smartphone navigation applications, and the methods of TQM are effective in analysing and enhancing digital navigation services. The results stress the need to minimize process variability, ensure the consistency of prediction, and the implementation of continuous improvement to increase customer satisfaction and service quality in modern navigation technologies.

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