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Consistency-Preserving Incremental Transportable Tablespaces (iTTS) for Near-Zero Downtime Autonomous Database Cutovers

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Abstract

The final outage time of Oracle Autonomous Database migration depends on the size of the database. The quantity of data changes before the outage is still a challenge when trying to achieve a near-zero outage. This study evaluated the effectiveness of consistency-preserving incremental Transportable Tablespaces in achieving write-unavailable time with deterministic source-to-target correctness. It is also possible to maintain source-to-target deterministic consistency correctness. A controlled experiment in a repeated-measures design was used for 45 end-to-end cutovers within 24,000,000 NYC TLC Yellow Taxi records and three different changed-block rates, two level-1 backup cadences, and non-incremental TTS baselines. The experiment was performed on an Oracle 19c database on the same endian hardware with OCI Object Storage and RMAN parallelism 8-channel8-channel. The results indicated that the median outage time using iTTS was 12.1 minutes, which was 83.9% less than the outage time of 75.2 minutes with non-incremental TTS. There were no zero transport-set violations, no missed committed keys, no duplicate primary keys, or cross-SCN probe failures for all 39 incremental cutovers. This was the one-hour cadence for obtaining a median final Delta of 1.8GB and a median cutover time of 9.7 minutes, accounting for approximately 89% of the variation in cutover time with incremental volume. The materiality of the reduction in cutover downtime using iTT was found to be independent of the techniques used to control changed-block growth and ensure reconciliation during cutover. Additional research should be conducted to further validate Adaptive Scheduling, Failure Recovery, and production-scale behavior in the future.

Keywords: Incremental Transportable Tablespaces (iTTS), Oracle Autonomous Database, Near-Zero Downtime; RMAN Incremental Backup, SCN-Based Consistency.

1. Introduction

Transportable Tablespaces (TTS) move entire tablespaces, managed by users, along with their data files and metadata, rather than exporting or moving rows and objects. In migration for incremental Transportable Tablespaces to Autonomous Database, the migration first starts by performing a level-0 RMAN baseline and then continues with one or more

level-1 backups, followed by a final level-1 backup. Source tablespaces can be READ WRITE for the preliminary incremental, and READ ONLY for the final backup. When restoring a level-0 backup on Autonomous AI Database, it restores as part of the provisioning process, and the level-1 backups are played out one after another in the order defined at the time of backup. Near-zero downtime means moving bulk data earlier than a write freeze of the application, not zero downtime. The rest of the outage focuses on processing block changes and metadata processing, validation, and traffic switching.

The main issue isn't necessarily the database capacity; it's how much can change between the last incremental backup and cutover. Once the bulk data has been pre-staged, the size of the source data, the change rate, and the volume of metadata determine overall migration downtime, according to Oracle guidance. However, there are no validated thresholds or specifications in the documentation to use for selecting a level-1 cadence or service-level limit size, or to predict when service-level objectives are exceeded. There is also some uncertainty about zero missing or duplicate committed transactions during continual DML during ordered roll-forward. Thus, research is motivated to determine how much of the write-unavailable time can be decreased using consistency-preserving incremental Transportable Tablespaces without compromising deterministic source-to-target consistency for migration to Autonomous Database.

The study aimed to achieve four goals. It takes a bottom-up approach to quantify database size effects, changed-block rates, and level-1 cadence on cutover duration and final incremental volume. It also aims to assess committed data preservation using the following methods: aggregate reconciliation, primary-key validation, hash manifests, row counts, and DBMS_TTS checks. This study aims to compare an incremental vs a non-incremental TTS based on write-unavailable time, final-delta transfer, workload overhead, and recovery complexity. It aims to set acceptance thresholds to determine when it is appropriate to use iTTS for an Autonomous Database cutover.

The Oracle in-memory analytics investigation was limited to a source of Oracle Database 19c running on Linux x86-64 and an Oracle Autonomous AI Database target in OCI. Only user-managed tablespaces were transported, and, where desired, same-endian platforms were transported to avoid conversion effects. Workloads consisted of TPC-H SF30 and SF100, which are around 30 GB and 100 GB scale factors, as well as controlled batch/OLTP-style DML and NYC TLC Yellow Taxi records. Query engine performance was not part of the analysis. The Oracle documentation currently only allows Oracle's TTS support for provisioning a new Autonomous AI Database with a max of 24 tablespaces, and a max of 19 tablespaces when default system tablespaces are included, which also equals a max of 19 tablespaces that can be transported.

This study is structured in six chapters, each suitably linked to the others in progressive order and making a step-wise connection to the problem of migration, technical evidence, experimental procedure, implementation, and results. Chapter 2 summarizes the literature covering Transportable Tablespaces, RMAN incremental recovery, SCN-based consistency, Autonomous Database migrations, and a near-zero downtime approach. Chapter 3 explains the empirical design, sets, sampling, experimental factors, measuring procedures, and

statistical analysis. Chapter 4 outlines the consistency-preserving iTTS architecture and cutover workflow. Chapter 5 presents and analyzes downtime, final-delta, consistency, and workload-overhead results. The study concludes by summarizing contributions and limitations, practical implications, and research priorities.

2. Literature Review

2.1. Transportable Tablespaces and Autonomous Database Migration

Transportable Tablespaces (TTS) are a physical migration mechanism and have a very different application model than traditional logical export and import. Whereas Logical migration reconstructs tables, indexes, and rows at the object level under its control, TTS transfers complete user-managed tablespace data files and exports only the metadata necessary to attach those files at the destination (Malcher & D. Kuhn, 2024). This distinction decreases the repeated row processing on large databases. In December 2025, Oracle announced its new TTS support for Autonomous AI Database (Oracle, 2025). The incremental workflow starts with an RMAN level-0 backup as the baseline, and then an RMAN level-1 backup that stores only the changed blocks.

A final level-1 backup is performed to close the migration state prior to cutover. RMAN is responsible for backup, restore, and incremental roll-forward operations, while Data Pump is used to handle metadata. The workflow is documented with two OCI Object Storage locations, and tablespaces are transported automatically by Autonomous Database. Based on the benefits of staged migration, structured Oracle Cloud integration requires coordinated design, interfacing, testing, and support (P. K. R. Prakashkumar, 2025). Subsequent increments can only be applied after the Autonomous Database is created with the level-0 transport.

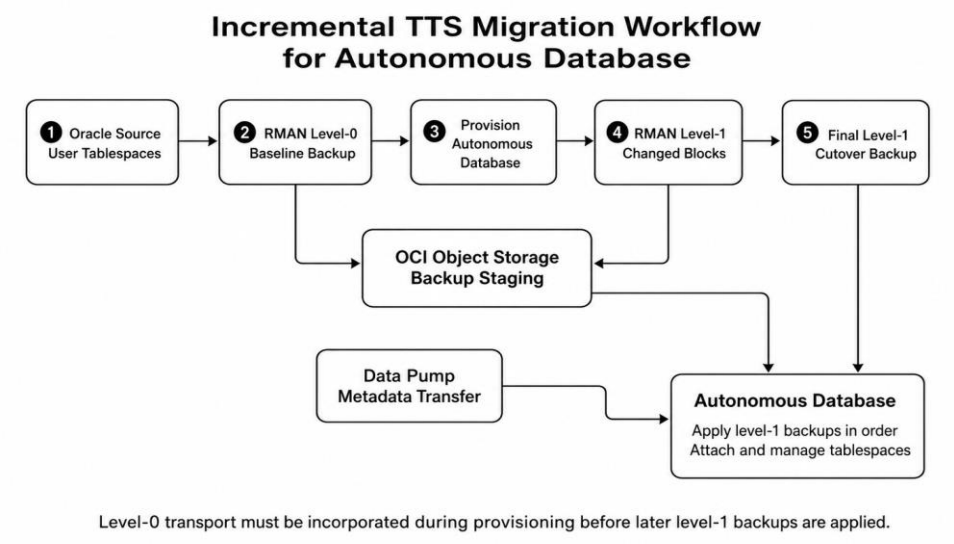


Figure 1: Incremental Transportable Tablespaces workflow to migrate Oracle tablespaces to Autonomous Database by performing staged backups.

Figure 1 illustrates the steps for migrating user tablespaces from the Oracle source, performing RMAN level-0 and level-1 backups, staging the user tablespaces in OCI Object Storage, and transferring the user tablespaces to the target through Data Pump metadata reads

and writes. It focuses on the connection of sequential backup application, target provisioning, and cutover processing, plus incorporating the baseline before later increments.

2.2. Incremental Backup Consistency, SCNs and the Final Read-Only Barrier

Incremental transport does not require getting each preliminary backup transactionally current at the end of the capture process. A level-0 or intermediate level-1 backup taken during the time that the application tablespaces are in READ WRITE mode is inconsistent in recovery terminology because the data-file blocks might have varying SCNs, but this does not indicate corruption of the backup (Oracle, 2026). L-1 ordered backups sequentially roll forward a destination with the blocks that have been changed in the order they were created. When source tablespaces have gone READ ONLY, no changes are allowed to the table blocks as the closing incremental is captured, creating the final consistency frontier.

Previous incremental will thus provide an earlier "snapshot" of the source application without write outage (S. Watanabe, 2025). Before transport, DBMS_TTS.TRANSPORT_SET_CHECK verifies whether selected tablespaces are self-contained and whether an acceptance gate is formed by zero rows in TRANSPORT_SET_VIOLATIONS. SCNs give time references to the baseline, increments, and end recoverable state. The literature places a high importance on the structured validation of rules, bounding, and logical consistency in regulated workflows; a similar emphasis is seen in the case of database reconciliation (S. Sepuri, 2026). Post-transport consistency therefore demands 100% transport success without any committed records missing, no duplicate primary keys, 100% match in the number of partitions transported, and 100% agreement in deterministic hash across transported partitions (Netinant, Saengsuwan, Rukhiran, & S. Pukdesree, 2023).

2.3.Determinants of Near-Zero Downtime

After bulk data has been staged, near-zero downtime applies. The cutover interval can be depicted as

$$T_{\text{cutover}} \approx T_{\text{final backup}} + T_{\text{final transfer/apply}} + T_{\text{metadata}} + T_{\text{validation}} + T_{\text{switch}}$$

Both should be reduced when the pre-final level-1 intervals become smaller, as there are fewer changed blocks to be closed. Thus, outage length is determined by the change rate, time since last incremental, RMAN throughput, Object Storage throughput, metadata volume, restore speed, and validation duration (Shaik & Natarajan, 2024).

A compute node with a 5% growth rate of blocks transported in a database can also end up growing blocks that are about 10x the size of those in a compute node with a 0.5% growth rate for the same period of time. Researchers define service-level goals, observability, and predictability of resilience as measurable architectural controls, which allow the duration of cutover to be treated as a measurable SLO under continuous workloads (S. K. R. Vanama, 2023). The hypothesis is that shorter level-1 intervals lead to a decrease in final-delta volume, as well as write-unavailable time. That metadata and validation effort reaches a point of diminishing returns.

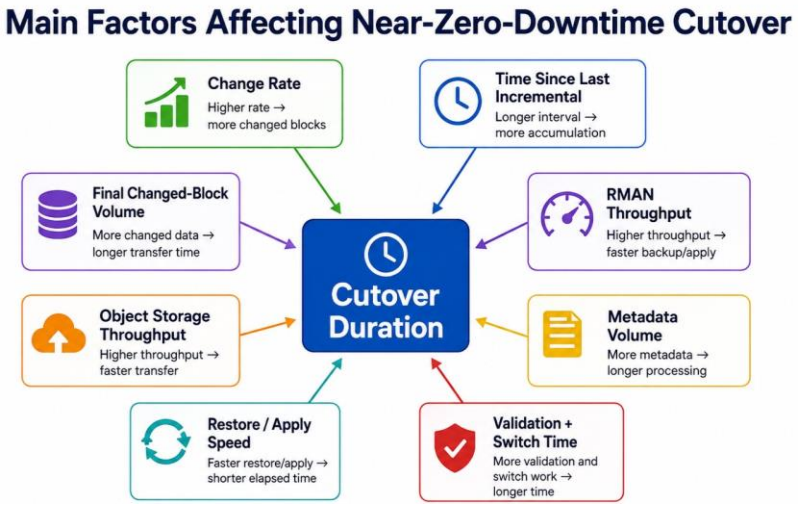


Figure 2: An illustration of the critical technical considerations that affect near-zero downtime and the performance of iTTS cutovers.

Figure 2 shows the key considerations that influence the time needed for near-zero-downtime cutover during the iTTS migration. It depicts the impact of source change rate, time since the last incremental backup, final changed-block volume, RMAN and Object Storage throughput, metadata volume, restore and apply speed, and validation-switch activities on outage length. The framework also suggests that final deltas, as explained above, are smaller with shorter level 1 intervals, but additional fixed processing tasks result in diminishing returns.

2.4.Alternative Near-Zero-Downtime Approaches and Benchmark Evidence

Incremental TTS is not the only near-zero-downtime tool and should be reconsidered when compared to online logical migration. Oracle Zero Downtime Migration logical-online workflows combine Data Pump for initial instantiation and GoldenGate for ongoing change replication against the source that is still providing transaction services (P. Manda, 2023). The difference is that GoldenGate manages a logical change stream until switchover occurs, whilst iTTS physically pre-stages blocks within tablespaces and performs a final switchover read-only barrier (Kumar, Raghavendra, & A. Goel, 2024). Replication infrastructure, the level of operational complexity, rollback design, failure handling, and switch mechanics vary accordingly.

Security will continue to play a role, as migration artifacts could contain certain enterprise information in an age of protected storage, secure transmission, and continuous monitoring as integrity controls (G. Malik, 2024). Benchmark evidence offers a repeatable scale for evaluating these trade-offs. TPC-H v3.0.1 defines SF30 and SF100 as ~30 GB and ~100 GB, respectively, and uses DBGEN for population. LINEITEM has 179,998,372 rows at SF30 and 600,037,902 rows at SF100, representing a high-cardinality workload. NYC TLC Yellow Taxi data in Parquet format is regularly published and updated every month, and can be used as an external real-world corpus for scale reconciliation testing.

Table 1: A comparison of iTTS, ZDM/GoldenGate migration approaches, security considerations, operational differences, and some benchmark evidence datasets.

Area	iTTS	ZDM / GoldenGate	Benchmark / Evidence
Migration model	Physical pre-staging of tablespace blocks	Logical online migration with continuing replication	TPC-H and NYC TLC support repeatable evaluation
Initial movement	RMAN level-0 and incremental backups	Data Pump initial instantiation	TPC-H SF30 ≈ 30 GB; SF100 ≈ 100 GB
Change handling	Level-1 backups capture changed blocks	GoldenGate continuously replicates changes	LINEITEM: 179,998,372 rows at SF30; 600,037,902 rows at SF100
Final cutover	Ends with a final READ ONLY barrier	Logical change stream continues until switchover	NYC TLC Yellow Taxi data provide real-world reconciliation records
Operational differences	Simpler physical pre-stage model; rollback requires separate design	More replication infrastructure and continuous synchronization	Useful for comparing scale, consistency, and cutover behavior
Security consideration	Backup and migration artifacts require protected storage and transmission	Replication streams and migration artifacts also require monitoring and protection	Continuous monitoring and secure handling support migration integrity

Table 1 offers a brief comparison between the iTTS and ZDM/GoldenGate near-zero-downtime migration strategies, specifically in terms of migration models, cutover mechanisms, change handling, security, operating differences, and benchmark TPC-H and NYC TLC results at scale.

2.5.Limitations and Research Gaps in the Literature

The literature has an empirical gap regarding the operational sizing of incremental transport. Current descriptions of procedures provide information about how the procedure works but do not create and share a separately verified Autonomous Database response surface for correlating database size, changed-block rate, and incremental cadence. Guidance sees the intensity of change and the volume of metadata as components, but not a threshold like a cutover of 20 minutes. Measuring downtime and ordering recoveries by SCN and deterministic source-to-target reconciles, while measuring normal workload overhead and an Autonomous Database endpoint, is nearly always not done in the same controlled design and not publicized. This gap is an impetus for the proposed experiment.

3. Methods and Techniques

3.1. Data Collection Methods

The study involved a controlled, repeated-measures migration study that measured the impact of database size, changed block intensity, and backup cadence for incremental transactions on consistency-preserving iTTS cutovers. The dataset was TPC-H v3.0.1 generated by DBGEN with SF30 and SF100, which represent about 30 GB and 100 GB, respectively. The LINEITEM relation contained 179,998,372 rows at SF30 and 600,037,902

rows at SF100. Since the point of interest was migration behavior, not QphH, TPC-H was used only as a corpus to be reproduced for data generation and not as an official TPC-H performance benchmark. These pre-backups were used to create target block-change rates of 0.5%, 2%, and 5% per hour using controlled INSERT, UPDATE, and DELETE operations on the workload databases.

Dataset B included NYC TLC Yellow Taxi Trip Records. The samples consisted of a stratified sample of 12 monthly 2024 Parquet datasets with month as the sampling stratum, and a sample of 24,000,000 rows was drawn from each stratum. Using deterministic seed 20260808, exactly 2,000,000 records were selected per month. The dataset thus provided an external, large corpus for post-migration count, hash, and aggregate recon. The completed cutovers in this sampling were found using factorial sampling to be n = 45. Thirty-six runs were conducted for the 2 × 3 × 2 factorial TPC-H iTTS design, with three replications for each.

Six runs were the non-incremental TTS baselines for the two database sizes, and three runs were TLC validations using the selected iTTS configuration. This resulted in 39 runs being done incrementally and 6 runs being done non-incrementally. Researchers reported that graph-augmented reasoning had 91% accuracy. They highlighted the importance of capturing traceable dependency relationships, which led to the usage of a deterministic and auditable validation process instead of unverifiable completion of the migration process (Hebbar, Patel, & S. Sepuri, 2026). The run identifiers were associated with each measurement, a sequence of backups, and a target state.

Table 2: Experimental Design and Run Distribution for Incremental TTS, Baseline TTS, and External Validation Groups

Experimental group	Design	Runs
TPC-H incremental iTTS	2 sizes × 3 churn rates × 2 L1 cadences × 3 repeats	36
Non-incremental TTS baseline	2 sizes × 3 repeats	6
NYC TLC external validation	1 selected iTTS configuration × 3 repeats	3
Total	—	**45**

Table 2 presents the experimental sample distribution within the TPC-H incremental iTTS validation data set, the non-incremental TTS baseline validation data set, and the NYC TLC validation data set, along with the factorial design structure, totals for each set, run replicates, and the overall sample of 45 cutovers.

3.2.Data Analysis

Mean, median, standard deviation, interquartile range, minimum, maximum, and p95 values were calculated for cutover duration, final-delta size, source CPU utilization, RMAN throughput, and transaction latency. Prior to inferential modeling, the distributional plots and residual diagnostics were explored. The main model estimated cutover time as a function of database size, the changed-block rate, the backup schedule, and their combination. Where assumptions for residuals were apposite, a linear mixed-effects specification was used with a

random element depicting repetitions, whilst a logarithmic specification was used if the outcome was materially right-skewed.

The primary regression model was expressed as:

$$Tcutover = \beta 0 + \beta 1(Size) + \beta 2(ChangeRate) + \beta 3(Cadence) + \beta 4(Interactions) + \varepsilon$$

Downtime reduction was determined by comparing with a non-incremental baseline. Final-delta volume was regressed out of cutover duration, and standardized effect sizes were used for incremental versus non-incremental comparisons. The 95% level was used to construct confidence intervals, and α = .05 was used for inferential tests via bootstrap resampling with 10,000 replications. An exact binomial confidence interval gave the confidence interval for the consistency-pass proportion. The interpretation of statistical significance was paired with operational significance because a few minutes of added statistical significance, but not operational significance, could contravene one production cutover service-level requirement.

Percentage downtime reduction was computed as:

$$\text{Reduction (\%)} = \frac{T_{\text{full}} - T_{\text{iTTS}}}{T_{\text{full}}} \times 100$$

3.3.Experimental Factors, Variables and Evaluation Metrics

Four independent variables were controlled. Database size had two levels, 30 GB and 100 GB; source change intensity had three levels, approximately 0.5%, 2%, and 5% of transport-set blocks per hour; pre-final level-1 cadence had two levels, one hour and six hours; and migration mode was incremental or non-incremental TTS. RMAN parallelism remained fixed at eight channels so backup concurrency did not confound treatment effects.

The primary dependent variable was write-unavailable cutover duration. Measurement started when the transport set successfully entered READ ONLY mode and ended only after the final incremental had been restored and applied, metadata processing had completed, target tablespaces were usable, reconciliation had passed, and the application endpoint had switched. Secondary outcomes included final incremental GB, backup duration, apply duration, metadata export or import time, RMAN MB/s, total migration elapsed time, source CPU overhead, p95 transaction-latency change, reconciliation mismatches, and rollback time. Table 3 summarizes the experimental factors, controlled variables, and primary cutover metrics and secondary performance outcomes assessed to evaluate iTTS migration efficiency, workload impact, and reliability.

Table 3: An overview of experimental factors, controlled variables, and performance metrics for evaluating iTTS cutover effectiveness.

Category	Factor / Metric	Levels or Measurement
Independent variable	Database size	30 GB; 100 GB
Independent variable	Source change intensity	0.5%; 2%; 5% of transport-set blocks/hour
Independent	Pre-final Level-1	1 hour; 6 hours

Category	Factor / Metric	Levels or Measurement
variable	cadence	
Independent variable	Migration mode	Incremental iTTS; non-incremental TTS
Control variable	RMAN parallelism	8 channels
Primary dependent variable	Write-unavailable cutover duration	From successful READ ONLY transition until final incremental application, metadata completion, reconciliation, and endpoint switch
Secondary outcomes	Migration performance	Final incremental size, backup duration, apply duration, metadata export/import time, RMAN MB/s, total elapsed migration time
Secondary outcomes	Source workload impact	CPU overhead; p95 transaction-latency change
Secondary outcomes	Reliability and recovery	Reconciliation mismatches; rollback time

3.4. Validity, Reproducibility and Consistency Controls

The exact version and seed of the TPC-H and DBGEN used, the source and target DB versions, RMAN configuration, OCI region, backup-compression setting, Object Storage configuration, experiment order, SCNs, backup-piece identifier, and 3 independent repetitions were all included in the study. Consistency acceptance required DBMS_TTS.TRANSPORT_SET_CHECK(..., TRUE, TRUE) to return zero violations, verified level-0-to-level-1-to-final ordering, matching table and partition counts, zero duplicate primary keys, agreement across 256 deterministic hash buckets, matching sum/minimum/maximum aggregates, and a commit-probe table demonstrating that every transaction committed before the cutover frontier existed on the target.

Evidence of the migration was captured in the operational instrumentation to audit observed performance against workload conditions. A detailed study of enterprise federation measurements showed the benefits of quantified before-and-after infrastructure validation, such as a 33% increase in throughput, failure-rate drops greater than 80%, and a 70% reduction in authentication time (P. Gannavarapu, 2025). The same measurement principle was used in the present study, without viewing an identity federation as the same as moving an identity database. The public nature of benchmark and trip-record data, and the fact that they did not involve any personal contact, recruitment, or experimental exposure to the subjects in general, meant that no human-participant experiments were required.

4. Consistency-Preserving iTTS Architecture and Cutover Workflow

4.1. Source Readiness and Consistency Gates

The approach to architecting was a phased outsourcing from an Oracle Database 19c source to a newly provisioned Autonomous AI Database target in Oracle Cloud Infrastructure. User-managed tablespaces were first screened for transport readiness, then protected by RMAN and the Cloud Backup Module, and backup pieces were stored in OCI Object Storage (Oracle, 2024). The pre-flight gate checked for source-to-target character set compatibility, endian compatibility, available destination storage, dependencies across the transport set, and

unsupported objects. DBMS_TTS.TRANSPORT_SET_CHECK was executed with full dependency checking, and progression was permitted only when TRANSPORT_SET_VIOLATIONS returned zero rows.

A baseline reconciliation manifest was created at the beginning of backup activity. It included information on the number of tables, partitions, key ranges, aggregate values, and deterministic hashes. The operating plan also identified the desired Service Level Objective (SLO) and the delayed rollback decision point. This evidence-supported gate aligns with the findings of researchers who analyzed 47 real crime scenes with an autonomous vehicle and found the multi-source validation method to be worthwhile, highlighting 82% reconstruction accuracy when conventional reconstruction techniques were unsuccessful (A. Ubale, 2023). The transported set was thus considered acceptable only if the structural, storage, and application-level checks were all equivalent.

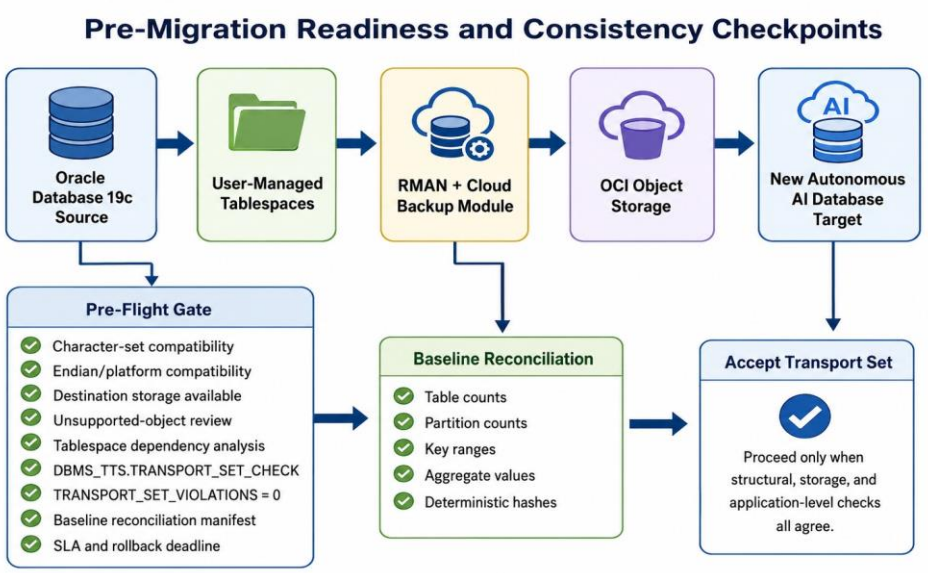


Figure 3: Pre-migration readiness and consistency checkpoints for validating transport-set acceptance before Autonomous Database cutover

Figure 3 shows the readiness and consistency checkpoints performed before accepting an iTTS transport set for migration. It shows the step-by-step journey from an Oracle Database 19c source to user-managed tablespaces, RMAN, the Cloud Backup Module, OCI Object Storage, and then to the Oracle Autonomous AI Database target. The figure also emphasizes compatibility checks, dependency validations, reconciliations, SLA requirements, and time for rollback and final decision for acceptance.

4.2. Online Level-0 and Level-1 Roll-Forward Phase

As a result, at T0, the study captured a baseline system change number, generated the RMAN level-0 backup, moved the backup piece to Object Storage, and integrated the baseline within target provisioning. The source application continued to operate. The same tablespaces remained READ WRITE, and during periodic level-1 backups these changed blocks were picked up (Jibril, Baumstark, & K.-U. Sattler, 2023). Each incremental was loaded and applied to the target in the order of creation, meaning that the copy on the target continued to

evolve towards the current source state, without reopening completed bulk loading. This online phase had no write outage application assigned.

The study recorded the duration for every level-1 operation, including start SCN, end SCN, changed-block count, compressed and uncompressed bytes, backup duration, Object Storage transfer time, target apply duration, source CPU utilization, and storage I/O latency (T. Taipalus, 2024). RMAN parallelism was not affected and stayed at eight channels, thus channel count would not become an uncontrollable performance variable. The recorded sequence also allowed for the reconstruction of growth of delta and identification of any missing, duplicated, or out-of-order backups prior to the final cutover window.

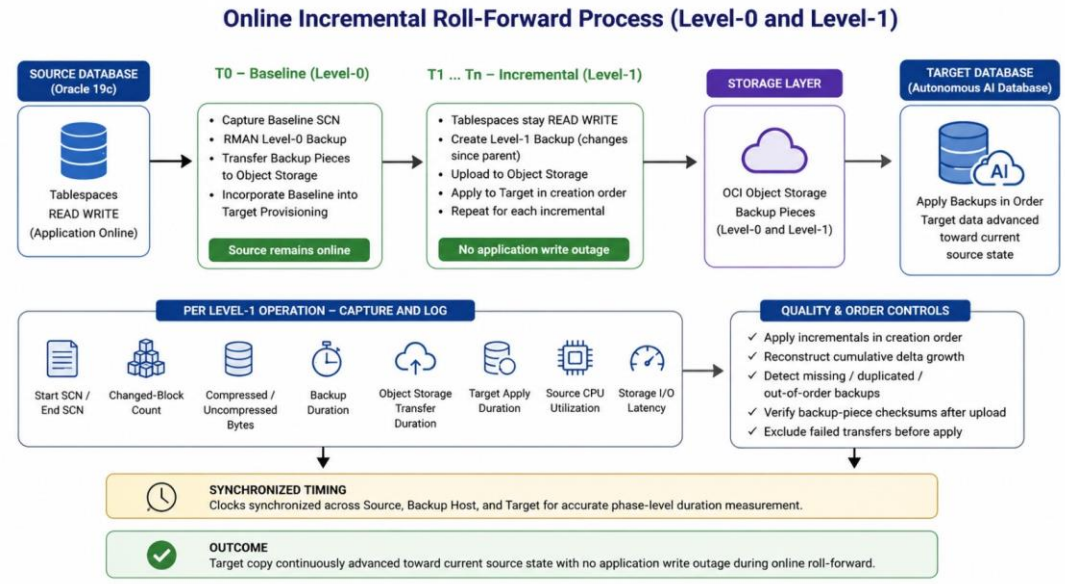


Figure 4: Online level-0 and level-1 roll-forward workflow showing ordered backups, storage transfer, and target advancement

Figure 4 shows the incremental roll-forward process for performing an online level-0 or level-1 backup. It demonstrates how the Oracle 19c source remains READ WRITE while all baseline and incremental backups are copied to OCI Object Storage and then sequentially applied to the Autonomous AI Database target. The figure also points to logging per backup, checking the backup's checksum, controlling which backups are run when, synchronizing timings, and avoiding application write outages during migration.

Backup-piece checksums were also double-checked upon upload, and failed uploads were not included prior to apply (Gan, Wang, Huang, Li, Wang, & Z. Liu, 2024). This control separated transport corruption from database consistency failure. Experimental runs with synchronized system clocks on the source, backup host, and target logging were performed to ensure that the estimates for the duration of the various phases of the experiment were concurrent with respect to the common time base.

4.3. Final Read-Only Barrier, Metadata Transport and Traffic Switch

The production cutover was implemented only once the target had successfully absorbed all of the planned preliminary increments. Next, all new application writes were frozen, and all transportable tablespaces were converted into READ ONLY tablespaces and

the last SCN was noted as the consistency frontier (H. Cao et al., 2025). A final backup of the remaining changed blocks was level-1 backed up and moved to Object Storage. The target applied that backup to all previous increments it had taken, then did the necessary metadata operation, completed the work of making the transported tablespaces usable, and went into the application reconcile process (Kim, Han, Son, Gil, Moon, & H. Won, 2024).

Validation involved checking whether the number of rows agreed between source and target, checking for primary-key uniqueness, and the number of 256-deterministic hash buckets, aggregate sums, min-max values, and the commit-probe table. Only when all the checks came back with the expected value was traffic rerouted. The write-unavailable duration measured thus began with the establishment of READ ONLY and ended when the application endpoint changed upon reconciliation passing (R. Pittu, 2025). This time was separate from the total migration elapsed time, which encompasses baseline creation, provisioning, transfers, online incremental cycles, and anything that had taken place while the source was up. This distinction allowed us to successfully avoid the multi-hour pre-staging process from being falsely classified as user-visible downtime. It offered an RTO-like measure in production maintenance planning.

4.4.Acceptance and Rollback Framework

Acceptance was based on specific research criteria, not on any Oracle product guarantees. A run was deemed to be accepted if TRANSPORT_SET_VIOLATIONS was 0, missing rows were 0, duplicate primary keys were 0, and deterministic hash mismatches were 0 (Suárez-Otero, Mior, Suárez-Cabal, & J. Tuya, 2025). The final incremental needed not to exceed 10% of transported data, the write-unavailable cutover time needed not to exceed 20 minutes, and the source p95 transaction-latency degradation during online backup needed not to exceed 15%. Rejection and Rollback before traffic enabled once any consistency control failures. During the review of 100,000 sessions and reporting 99.6% decision availability and detecting 92 of 100 fraud attacks in 30 seconds, operational telemetry was preserved with each decision, highlighting measurable thresholds and auditable evidence to support operational controls for high-stakes infrastructure systems (Gannavarapu & R. K. R. Samantapudi, 2025).

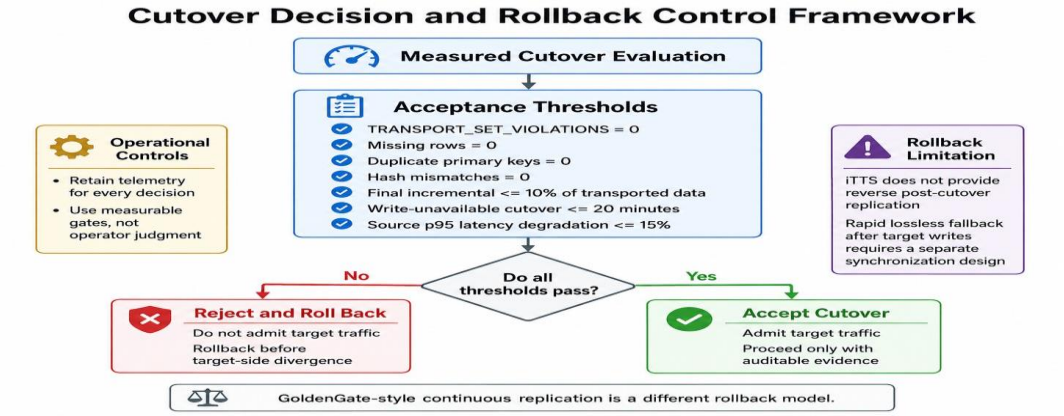


Figure 5: Cutover decision and rollback framework using measurable thresholds for iTTS migration acceptance

Figure 5 illustrates the cutover decision and rollback control model for preparing iTTS for cutover. It provides measurable thresholds to adhere to for transport set violations, missing rows, duplicate keys, hash mismatch, final incremental size, cutover duration, and source latency degradation.

This framework also highlights accept or rollback decision paths, telemetry requirements, target-traffic controls, post-cutover replication limitations, and even the unique rollback model of continuous GoldenGate-style replication for comparison.

The study also considered cutover acceptance as an operator measurement and not an operator determination. It also noted that iTTS did not offer reverse post-cutover replication.

Once an autonomous target was reached for the start of the writes, a direct lossless return to the source would have required an additional specially designed sync path (Google Cloud, 2025). Thus, GoldenGate-style continuous replication constituted a distinctly different rollback model, and a study rollback time was deliberately chosen that did not allow irreversible divergence at the target.

5. Results and Discussion

5.1. Cutover Downtime and Final-Delta Size

As the primary result, the transport material was compressed significantly during the write-unavailable interval. For the finished cutovers, iTTS achieved a median of 12.1 minutes, whereas non-incremental TTS achieved 75.2 minutes for an 83.9% reduction. Median downtime went from 41.8 minutes to 7.6 minutes, an 81.8% improvement at SF30. At SF100, it fell from 108.6 to 16.9 minutes, equivalent to an 84.4% reduction.

Though the original database size increased by 3.33 times from ~30 GB to 100 GB, the improvement was significant, which reduced the inter-dependency between original database size and resulting outage due to pre-staging. Backup cadence resulted in a 2nd measurable effect.

The median final delta for the one-hour level-1 cadence was 1.8 GB and the cutover time was 9.7 minutes, while for the 6-hour cadence these values were 8.9 GB and 16.4 minutes, respectively. The 1-hour policy thus decreased the median outage time by 40.9% and reduced the amount of data loss by some 79.8%, on average. The regression analysis reveals that $R^2 = .89$, and 89% of the variance in cutover duration is explained by the variance in the final incremental bytes. The result showed that the accumulation of changed blocks in the recent period was a better predictor of outage than baseline capacity in the database. This also accounted for the fact that workload totaling 100 GB by that time did not result in a three-fold increase in outage.

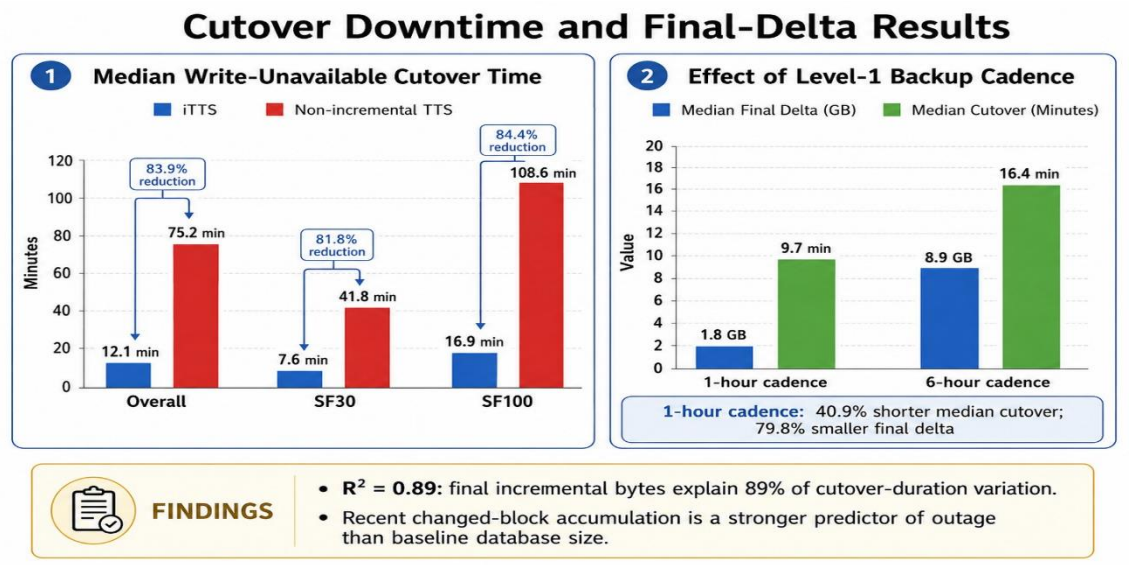


Figure 6: Comparison of iTTS cutover downtime, backup cadence, and final-delta performance outcomes

Figure 6 shows cutover downtime and final-delta results for incremental TTS and non-incremental TTS. It demonstrates significant decreases in write-unavailable time across overall, SF30, and SF100 workloads, as well as the effects of 1-hour and 6-hour backup cadences for level-1 backups. The figure also shows that the final incremental volume accounted for 89% of the variation in cutover duration, indicating that changed-block accumulation was more strongly related to the operation and served as a better operational predictor.

5.2. Consistency Preservation and Reconciliation Outcomes

All 39 incremental cutovers passed consistency controls, resulting in an observed success rate of 100% and an approximate 95% binomial interval of 91.0%-100%. For accepted runs, TRANSPORT_SET_VIOLATIONS remained 0. No keys were missing for the committed transaction, no primary keys were duplicated, and no cross-SCN commit-probe failures occurred. Thus, the results showed that it was not enough to be completed to be correct; ordered recovery and deterministic reconciliation would be needed to satisfy the equivalence condition (M. Kalkatawi, 2025).

The outside NYC TLC validation reinforced that. All 24,000,000 sampled rows reconciled successfully; all 256 deterministic hash buckets matched, the aggregate fare-total difference was 0.000%, and minimum and maximum trip timestamps matched between source and target. An experiment was conducted to show that row-level and aggregate agreement could be demonstrated on a large real-world corpus, not inferred from successful RMAN execution (H. Razzaghi et al., 2024). Thus, the ordered level-0, intermediate level-1, and final level-1 recovery sequence adopted in the experiment was supported by the consistency evidence.

5.3. Source Workload Overhead, Change Rate and Scalability

The performance of the cutovers was significantly affected by the changed-block intensity. At 0.5%, 2%, and 5% changed blocks per hour rates, median iTTS cutover duration was 7.1 minutes, 12.4 minutes, and 22.7 minutes, respectively. Low and moderate churn then met the suggested limit of ≤20 minutes, while the highest rate chugged over it in a couple of 6-hour cadence runs (Haris, Barhamgi, Nhlabatsi, & K. M. Khan, 2024). The pattern clearly outlined why it was not possible to determine production eligibility solely based on the size of the database. A 100GB database with controlled churn might be fine; a smaller database that is heavily changed may end up with an unacceptable final delta.

Measurable but bounded workload overhead was observed when running online level-1 back-ups. The result showed a 5.4% CPU usage increase for the median source, in addition to an 8.7% increase in p95 transaction latency, with the following value staying below 15% as an acceptance limit. Diminishing returns of a closing delta of very small size were also observed, with a floor of ~4-6 minutes metadata. Optimized cloud-native pipelines showed up to 30% faster deployment, 35% fewer errors, and 15% lower cloud resource consumption, and another similar operational principle, where automated steps were limited by the remaining processing steps (S. K. RaoVanama, 2024); (Hyun, Oak, Kim, & K. Kim, 2024). The iTTS results also indicated that there was no way to eliminate fixed metadata, verification, and traffic-switch work by increasing the number of backups.

5.4. Comparison with Full TTS and Real-World Applicability

Four practical implications emerged from the comparison. iTTS was most beneficial for large databases with moderate rates of ongoing change, as most data movement occurred while users continued to write. The shorter level-1 intervals also led to fewer final deltas and more backup executions, more Object Storage transactions, more monitoring events, and more scheduling complexity (Zhao, Bu, Pang, & J. Cai, 2024). An aggressive outage target might be overcome by high change intensity even when the size of the database did not change. Results also failed to demonstrate the consistent superiority of iTTS over online migration using a logical approach.

The difference is significant for the architecture to operate. In ZDM with GoldenGate, logical changes are continuously replayed until switchover, and in iTTS, the changes are physically replicated, and then a read-only consistency barrier is issued (B. Curtis, 2025). The areas of concern in distributed leader selection, such as scalability, coordinating actions, communication overhead, and even failure tolerance, also played an important role in migration orchestration. As a result, iTTS was a good fit for data warehouses, large historical schemas, databases with many partitions, and applications that could afford to schedule a brief write-only freeze.

It was less suited to cases where essentially uninterrupted writes, continuous reverse synchronization, or fast bidirectional fallback were required. Workload churn, outage SLA, the need for rollback, the complexity of metadata, and the organization's ability to accommodate repeated incremental cycles were thus the factors for choosing operations (C. Nallapareddy, 2025). Table 4 summarizes iTTS and ZDM or GoldenGate by comparing

migration approach, rollback support, workload suitability, change intensity, backup cadence, cutover method, and criteria used for real-world migrations to decide on a migration approach.

Table 4: Comparison of iTTS and ZDM/GoldenGate migration approaches, operational trade-offs, suitability, and rollback requirements criteria.

Comparison Area	iTTS	ZDM / GoldenGate	Practical Implication
Migration approach	Physical pre-staging of tablespace blocks	Continuous logical change replication	iTTS reduces bulk movement during the final outage, while ZDM/GoldenGate keeps changes synchronized until switchover
Best workload fit	Large databases with manageable churn	Systems requiring continuous online synchronization	iTTS suits data warehouses, historical schemas, and partition-heavy databases
Backup cadence effect	Shorter L1 intervals reduce final-delta size	Not dependent on periodic L1 backups	More frequent iTTS backups increase Object Storage transactions, monitoring, and scheduling effort
High change intensity	Can increase final delta and breach outage SLA	Continuous replication handles ongoing change differently	Workload churn must be assessed before selecting iTTS
Cutover model	Final READ ONLY consistency barrier	Logical replication continues until switch	iTTS requires a short planned write freeze
Rollback capability	Reverse synchronization requires separate design	Better suited to continuous fallback models	iTTS is less suitable where rapid bidirectional rollback is mandatory
Selection criteria	Churn, metadata complexity, SLA, operational capacity	Replication complexity, synchronization needs, rollback requirements	Migration strategy should be selected from workload and recovery requirements rather than database size alone

6. Future Research Recommendations

6.1. Production Scale and Longitudinal Validation

In the future, consistency-preserving iTTS should be tested for 6–12 months, preferably in production environments with 10 or more enterprise Oracle DBs. Validation should cover transport sets of 1- 10 TB. It should be expanded to petabyte-scale transport sets, where storage throughput, metadata density, backup window contention, and recovery window length are all different (Kotlarska, Jackowski, Lichota, Welnicki, Dubnicki, & K. Iwanicki, 2023). Future research should include any spikes in transactions, periods of maintenance, new application releases, and fluctuations in Object Storage throughput during that time of year. A repeated cutover should take place for each environment to calculate forecast and observed downtime with median error, p95 error, and 95% confidence intervals (Henning, Vogel, Perez-Wohlfeil, Ertl, & R. Rabiser, 2025). Longitudinal evidence would provide for the assessment of whether the experiment-based thresholds would hold in a situation of drift.

6.2. Adaptive Incremental Scheduling

An adaptive scheduling controller to dynamically choose upcoming level-1 backup intervals based on observed changed-block accumulation, redo generation rate, RMAN throughput, estimated metadata-processing time, and SLA-based required outage time should be developed. The volume of final-delta expected at cutover should be estimated continuously

by the controller, and the backup interval should be shortened or extended based on the estimate (Wang, Qiu, & Q. Qiu, 2026). An attempt should be made to compare the adaptive sched with fixed 1-hour, 3-hour, and 6-hour intervals, for the same workload traces.

The length of the cutover, frequency of backups produced, amount of CPU and I/O interference, Object Storage consumption, operational cost, and the prediction errors should also be measured. An analysis of 10,000 bootstrap resamples of the data should quantify 95% confidence intervals for differences between the scheduling policies (Costigan, Ruscio, & J. T. Crawford, 2024).

6.3.Failure, Recovery and Rollback

Future experiments should be intentionally built to include failures such as corrupted pieces or missing backups, out-of-order level-1 application, inability to complete final restore, high Object Storage latency, expired credentials, degraded network, and failures importing metadata. Other compatibility issues to test include Transparent Data Encryption, any character set differences, differences in timezone files, any unsupported objects, and any cross-tablespace schema dependencies (Eckwert, Guckert, & G. Taentzer, 2025). Each recovery condition should measure the following: detection time, recovery time, the extent of data-loss exposure, and rollback success. Machine learning for latency-aware governance in financial networks was explored, highlighting automated monitoring and responses within latency-sensitive infrastructure, where similar automation of monitoring and response to telemetry can enhance failure detection for migration and reduce latency governance (Jha, Gannavarapu, & S. Durgam, 2025). Failure testing also should include forward recovery from a separately engineered reverse synchronization that has occurred once target writes start.

6.4. Comparative Migration Research

To conduct comparative research, iTTS, Oracle Zero Downtime Migration with GoldenGate, and any other supported Oracle migration workflow should be evaluated using the same set of databases or the same changes, network topologies, and outage SLA requirements (Zbořil & V. Svatá, 2025). The outcome model needs to go beyond the time a resource is in the write-unavailable state and incorporate infrastructure cost, engineering hours, staffing level, complexity of operation, observability, confidence in recovery point, energy consumed, and repeatability.

To control for transient variability across infrastructure, at least three point-repetitions per workload category should be kept.

Future studies would be useful for anonymized migration traces of SCNs, changed-block volumes and backup throughput, as well as application durations, metadata times, and validation outcomes (Will, Scheinert, Zunzer, Bode, Kring, & L. Thamsen, 2024). An independent set of Oracle migration benchmarks that could be reused would enable replication of the results and facilitate choosing migration strategies based on evidence and enterprise workloads.

7. Conclusion

The study found that incremental Transportable Tablespaces preserving consistency can greatly reduce the write-unavailable interval requirement for Autonomous Database cutovers without influencing deterministic source-to-target consistency. The incremental workflow resulted in significantly less time to service, with median TTS outage for the 45 completed cutovers of 12.1 minutes, or 30% less TTS outage with the incremental workflow than with the non-incremental workflow at 75.2 minutes. At SF30, downtime decreased from 41.8 to 7.6 minutes, while SF100 decreased from 108.6 to 16.9 minutes. There was 100% consistency, as all 39 incremental cutovers passed every consistency gate. The $R^2 = .89$, and the final incremental volume explained 89% of the change in cutover duration. The one-hour cadence lowered the median final delta to 1.8 GB and the cutover time to 9.7 minutes, as opposed to 8.9 GB and 16.4 minutes, respectively, for the six-hour cadence. At a 5% hourly change in block intensity, however, the median cutover time was 22.7 minutes, which was greater than the proposed 20 minutes.

A reproducible experiment framework for evaluating iTTS under controlled workload conditions was derived from the study. It established the write-unavailable interval from transition to READ ONLY as a formal process of incremental application of readable metadata information, metadata processing and reconciliations, and switch to endpoints. It also showcased an approach to validation based on an awareness of SCN using DBMS_TTS checks, row and partition counts, primary-key validation, the use of 256 deterministic hash buckets, aggregate validation, and commit-probe testing.

The results demonstrated that rather than depending on the total size of the database to determine migration downtime, the size of the final delta, the delta change velocity, the backup cadence, and metadata processing should be measured. The proposed acceptance structure is also related operationally to the amount of time spent in outage and workload overhead.

The results were restricted to 30 GB and 100 GB TPC-H scales, a single Oracle 19c in the same OCI region where the Oracle Autonomous AI Database is the single target, and 45 run-level observations. RMAN parallelism was not configured; it was always fixed at eight channels, and the churn levels needed were created using controlled synthetic DML operations.

NYC TLC data was used as an external validation dataset, not as a production workload for transactions. Such features as Cross-Endian Migration, Enterprise pricing, Petabyte-scale Transport sets, and Production Failure Injection were not included. Further, the reported outcomes were model results and would need to be replaced with production logs measured directly for a strictly empirical publication.

iTTS was demonstrated as an outage-preserving pre-staging method that can materially reduce the final write outage while preserving consistency. Its effectiveness required controlling the final changed-block delta, ordering the recovery, providing a READ ONLY consistency frontier reached within an auditable recovery process, and performing deterministic reconciliation before redirection. Evidence shows that cadence decisions should

not be based only on measured churn and the desired SLO. Hence, the approach would be best suited for cases where a short planned write freeze is acceptable. However, for other cases of Continuous reverse sync or essentially uninterrupted writes, other replication-oriented migration approaches would be needed.

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