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(RESEARCH ARTICLE)

A power BI clinical dashboard for data-driven decision-making in palliative care: A case study of hospice of the valleys

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Abstract

Palliative care providers face growing patient demand alongside constrained staffing and funding, yet many organisations still rely on manual, spreadsheet-based reporting that offers little real-time visibility into caseload, resource use, or outcomes. This paper reports the design, development, and evaluation of an interactive clinical dashboard, built in Microsoft Power BI, for Hospice of the Valleys, a community palliative care provider in Wales. Guided by the CRISP-DM framework, three operational datasets (community care, day-centre, and hospital support) covering 2020–2024 were extracted from the CANISC and ICARE clinical systems, cleaned, integrated, and modelled into a star-schema data model. The resulting dashboard tracks key performance indicators including total patients, total visits, average length of care, mortality rate, and professional workload across four interactive pages. Applied to 487 patients and 2,498 recorded visits, the dashboard revealed a marked rise in new referrals (from 4 in 2020 to 264 in 2024), a near-even gender split (55% female, 45% male), a 52% prevalence of cancer diagnoses, an overall average length of care of 162 days, and a 34% mortality rate. The dashboard enabled dynamic filtering by care setting and time period, supporting operational planning and funding-evidence needs. The paper situates these findings within the wider clinical-dashboard literature, discusses the practical and ethical implications of the design choices made, and proposes future work centred on predictive analytics, expanded data capture, and real-time alerting. The study demonstrates that a modestly resourced palliative care provider can derive substantial decision-support value from commodity business-intelligence tooling when data governance and stakeholder engagement are prioritised throughout development.

Keywords: Clinical dashboard; Palliative care; Power BI; Data visualisation; Hospice; Key performance indicators; CRISP-DM; Healthcare data analytics

1. Introduction

The healthcare sector has undergone substantial digital transformation over the past two decades, with clinical dashboards emerging as a central tool for translating raw patient data into timely, actionable information (Martinez et al., 2018). Clinical dashboards are interactive visual displays that aggregate key performance indicators (KPIs) and metrics relevant to patient care, operational efficiency, and quality improvement, allowing healthcare professionals immediate access to critical information for decision-making (Stadler et al., 2016; Bach et al., 2022).

This need is particularly acute in palliative care, where the timeliness and personalisation of care directly affect patient comfort and dignity at the end of life. Demand for palliative care services continues to grow as populations age and chronic illness becomes more prevalent, yet many providers, including community hospices, must meet this demand with limited staff and funding (Kamal et al., 2015). Hospice of the Valleys, a palliative care provider in South Wales, exemplifies this challenge: prior to this project, patient information was distributed across manual systems and static

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spreadsheets that were poorly suited to real-time analysis, making it difficult for administrators to track patient outcomes, allocate staff efficiently, or demonstrate the impact of the service to funders.

Data visualisation tools such as Microsoft Power BI have been proposed as a practical means of addressing this gap by consolidating disparate clinical data sources into a single interactive platform (Bach et al., 2022). This paper reports the design, development, and evaluation of such a dashboard, built specifically for Hospice of the Valleys, using the Cross-Industry Standard Process for Data Mining (CRISP-DM) as a guiding methodology. The remainder of the paper is organised as follows: Section 2 reviews the literature on clinical dashboards and their application in palliative care; Section 3 details the methodology, including data sources, cleaning, modelling, and dashboard design; Section 4 presents the results; Section 5 discusses their implications; and Section 6 concludes with limitations and recommendations for future work.

1.1. Aim and Objectives

The study aimed to design and implement a clinical dashboard using Microsoft Power BI to enhance palliative care and resource management at Hospice of the Valleys. Four objectives guided the work: (1) to identify KPIs relevant to palliative care and resource management, including patient care trends, resource allocation, and professional workload; (2) to design and develop a Power BI dashboard integrating data from the CANISC and ICARE systems for real-time KPI visualisation; (3) to evaluate the dashboard's effectiveness in supporting data-driven decision-making, patient outcomes, and resource management; and (4) to support funding applications through data-driven evidence of operational efficiency and service impact. These objectives were framed around a single research question: how can a clinical dashboard improve palliative care and resource management within the healthcare sector?

2. Literature Review

2.1. Evolution and Key Features of Clinical Dashboards

The concept of the clinical dashboard traces back to the balanced scorecard introduced by Kaplan and Norton in the early 1990s, subsequently adapted to healthcare alongside the rise of electronic health records and the quality-improvement movement (Kumar et al., 2024). Contemporary dashboards have moved beyond static reporting toward interactive, real-time displays that integrate patient-reported outcomes (Hartzler et al., 2015), large-scale statistical and treatment-plan data (Mayo et al., 2017), and Bayesian decision-support models (Mould et al., 2016). Dowding et al. (2015) characterise effective dashboards as offering a clear, immediate snapshot of vital data that facilitates decisive action, a definition echoed by Stadler et al. (2016), who describe dashboards as interactive visual displays used to monitor patient-care processes.

Across the literature, several recurring design features distinguish effective clinical dashboards: real-time data presentation that supports timely intervention (Waitman et al., 2011); user-friendly, customisable interfaces that reduce cognitive load for clinicians (Khairat et al., 2018; Daley et al., 2013); seamless integration with existing health-information systems (Dowding et al., 2015); clear visual encoding through colour and chart type (Weggelaar-Jansen et al., 2018); and drill-down capability that allows users to move from summary metrics to underlying detail (Stadler et al., 2016).

2.2. Types of Clinical Dashboards and Their Application

Dashboards can be broadly categorised as data-analytic dashboards for quality improvement (Khairat et al., 2018), operational dashboards for monitoring patient flow and resource use (Buttigieg et al., 2017), clinical decision-support dashboards providing patient-specific guidance (Dowding et al., 2015), population-health surveillance dashboards (Concannon et al., 2019), and patient-facing dashboards that support self-management (Daley et al., 2013). This typology reflects the versatility of dashboard technology across the care continuum, from bedside decision-making to public-health monitoring and organisational strategy.

2.3. Clinical Dashboards in Palliative Care

Within palliative care specifically, dashboards have been used to monitor patient symptoms, well-being, and pain in near real time. Bonsignore et al. (2018) evaluated the TapCloud telehealth dashboard, finding that it improved communication between patients and care teams and supported more responsive pain management. Harding et al. (2021) integrated a mobile-linked dashboard into home-based palliative care in resource-limited settings, improving accessibility and continuity of care. Ludlow et al. (2021) describe the co-design of a predictive-analytics dashboard for aged and palliative care that incorporated stakeholder feedback throughout development, while Bowers et al. (2023)

applied a machine-learning model within a dashboard context to predict mortality risk and trigger earlier palliative-care referral in a Medicare Advantage population. Collectively, these studies indicate that dashboards tailored to palliative care can improve interdisciplinary communication, symptom tracking, and the timeliness of referral, though most implementations remain descriptive rather than predictive in nature.

2.4. KPIs and Metrics in Palliative Care Dashboards

Selecting appropriate KPIs is central to dashboard design. Tang et al. (2021) highlight pain-management effectiveness, symptom-intervention frequency, and patient mobility as core postoperative and palliative metrics, while Patterson Silver Wolf et al. (2020) demonstrate the value of tracking treatment retention and adherence in a comparable clinical-tracking context. Bowers et al. (2023) identify resource-allocation metrics such as bed occupancy, staff workload distribution, patient acuity, and length of stay as essential for hospice-level planning, and Lim et al. (2022) argue for dashboards that integrate patient-reported outcomes alongside organisational performance indicators to provide a holistic, patient-centred view.

2.5. Benefits, Challenges, and User Experience

Empirical evidence supports the operational value of clinical dashboards: Waitman et al. (2011) report a 24% reduction in central-line-associated bloodstream infections following dashboard deployment, and Weggelaar-Jansen et al. (2018) document improved quality-improvement focus and inter-professional communication in Dutch hospitals using quality dashboards. User-centred design is repeatedly identified as decisive for adoption; Martinez et al. (2018) show that a design-sprint approach involving end users significantly improved usability and satisfaction for a patient-facing diabetes dashboard, while Gremyr et al. (2020) argue that iterative, user-involved design is necessary given the diverse and sometimes conflicting needs of healthcare staff. Conversely, poorly designed dashboards risk information overload (Khairat et al., 2018), and adoption can be undermined by resistance to change, inadequate training (Weggelaar-Jansen et al., 2018), and difficulty integrating heterogeneous data sources of variable quality (Dowding et al., 2018).

The COVID-19 pandemic accelerated dashboard adoption across public health, illustrating both the value and the design demands of dashboards under crisis conditions: Ibrahim et al. (2020) describe a clinical-intelligence dashboard used to optimise resource allocation during the pandemic, and Ivanković et al. (2021) assessed 158 public COVID-19 dashboards, concluding that clear visual design and usability were decisive for actionability. Suraj et al. (2022) similarly developed a decision-support tool to guide COVID-19 treatment, including the timely initiation of palliative care.

2.6. Gaps and Future Directions

Despite this progress, several gaps persist. Kamal et al. (2015) and Lim et al. (2022) note the limited exploration of artificial intelligence, machine learning, and Internet-of-Things integration for predictive analytics within palliative-care dashboards. O'Mahony et al. (2020) highlight persistent usability barriers and resistance to change among clinical staff, while Waller et al. (2019) point to unresolved ethical and privacy questions surrounding patient data used in dashboard systems. These gaps directly inform the design choices and limitations discussed later in this paper.

3. Methodology

The dashboard was developed using the Cross-Industry Standard Process for Data Mining (CRISP-DM), a widely used framework for structuring data-driven projects around business understanding, data understanding, data preparation, modelling, and evaluation. This framework was selected because it explicitly incorporates stakeholder consultation at each phase, which was essential given the sensitivity of palliative care data and the need for the final dashboard to match the operational language and priorities of hospice administrators.

3.1. Business and Data Understanding

The initial phase established the project's objectives, described in Section 1.1, through consultation with hospice administrators and clinical staff. Data were then sourced from three palliative care services delivered by Hospice of the Valleys: community care, day-centre care, and hospital support. Datasets were extracted from two clinical systems, CANISC and ICARE, and supplied as Microsoft Excel files covering patient records from 2020 to 2024. Table 1 summarises the structure of the three source datasets.

Table 1 Structure of the three source datasets (2020–2024)

Dataset	Columns	Rows	Notes
Community care	34	1,442	Core demographic, diagnosis, discharge and contact fields
Day-centre care	35	333	Includes an additional 'intervention' field not present elsewhere
Hospital support	33	882	Covers patient care delivered in hospital settings

3.2. Data Preparation

The three datasets were imported into Power BI via Power Query using a standard Extract-Transform-Load process. Data types were reviewed and standardised (date fields as Date/Time, identifiers and categorical fields as Text, age as Whole Number), a Source column was added to preserve provenance, and the datasets were appended into a single unified table. After cleaning, 27 columns were retained across patient identifiers, demographics, diagnosis, care dates, discharge outcome, and professional contact fields.

3.2.1. Duplicate handling

Records sharing a patient identifier but with distinct contact dates were retained rather than removed, since each contact date represented a discrete clinical interaction relevant to visit-frequency and professional-workload metrics; removing them would have understated true visit counts.

3.2.2. Missing values

Missing-value treatment was tailored to field sensitivity. Columns with extensive incompleteness that could not be safely imputed in a clinical context, such as Ethnic Group, postcode, and ICD-10 diagnosis code, were removed rather than filled, to avoid misrepresenting sensitive or diagnostic information. Where pcsvenddate (care end date) was missing, this was interpreted as an indicator of ongoing care rather than a data error; the current date was substituted only for the purpose of calculating an ongoing Length of Care, leaving the underlying end-date field unchanged. Attendance was set to 'Not Recorded' where contact occurred without an explicit attendance flag; fields describing discharge method, discharge location, and professional involvement were left unchanged when missing, to avoid overrepresenting particular categories.

3.2.3. Resolving inconsistencies

DAX-based calculated fields were created to reconcile conflicting entries between discharge method and discharge status. A Corrected Discharge Status field harmonised cases where one field indicated death and the other did not, and a Patient Status field classified each patient as Alive, Deceased, or Inconsistent (flagged for manual review), following the general approach to standardising patient-outcome coding described by Stadler et al. (2016).

3.3. Data Modelling

A star-schema data model was built around a central Main Dataset fact table, related to a Patient dimension table (one-to-many, ensuring each patient was counted once regardless of contact frequency), a Source dimension table (one-to-many, enabling filtering by care setting), and a Date dimension table (one-to-many, supporting time-based drill-down). This structure avoided duplication in aggregate metrics such as Total Patients and Average Length of Care while preserving the full interaction history needed for visit- and workload-based metrics.

3.4. Measures and Key Performance Indicators

DAX measures were developed for the principal KPIs identified during the business-understanding phase and cross-referenced against the literature (Stadler et al., 2016; Bowers et al., 2023). Table 2 summarises the core measures implemented.

Table 2 Core DAX measures implemented in the dashboard

Measure	Definition
Total Patients	Count of unique Patient No, ensuring each patient is counted once regardless of the number of recorded interactions.
Total Visits	Count of recorded Contact entries, including interactions with missing contact dates, to avoid undercounting engagement.
Average Length of Care	Mean of (pcsvenddate − pcsvstartdate); current date substituted for missing end dates to reflect ongoing care.
Mortality Rate	Count of deceased patients (Corrected Discharge Status = Died) divided by Total Patients.
Cancer Prevalence	Count of patients with a cancer-flagged diagnosis divided by Total Patients.
Professional Workload	Count of contacts grouped by Lead/Contact Professional, used to assess workload distribution.
Attendance Rate	Proportion of recorded contacts marked Attended versus Not Recorded or Other.

3.5. Dashboard Design and Structure

The dashboard was organised into four pages, each addressing a distinct analytical purpose identified through stakeholder consultation: (1) Overview, presenting headline KPIs (Total Patients, Total Visits, Average Length of Care, Mortality Rate), yearly intake trends, gender distribution, and top diagnosis groups; (2) Demographics, detailing age, gender, and cancer-prevalence breakdowns; (3) Patient Outcome, covering alive-versus-deceased status by age and gender, discharge trends, and discharge-status categories; and (4) Resource Allocation, covering attendance breakdown, professional contact volume, and a diagnosis-by-age-group heatmap. All pages share a Source slicer (community, day-centre, hospital support) and a Date range slicer, enabling dynamic, cross-filtered exploration consistent with the interactivity and drill-down principles emphasised by Stadler et al. (2016) and Bach et al. (2022).

3.6. Ethical Considerations

All patient data were anonymised prior to analysis, consistent with GDPR and applicable healthcare data-protection requirements; no personally identifiable information was used, and the pre-existing, routinely collected nature of the data meant that informed consent was assumed under the hospice's existing data-governance arrangements. Missing values were handled, as described above, to avoid misrepresenting patient-care status, reflecting the ethical caution urged by Waller et al. (2019) regarding the use of patient data in dashboard systems.

4. Results

The unified dataset comprised 487 patients and 2,498 recorded visits across the three care settings between 2020 and 2024. This section summarises the principal findings generated by the dashboard across patient demographics, diagnosis and outcomes, and resource allocation.

4.1. Patient Demographics and Intake Trends

Of the 487 patients, 55% (269) were female and 45% (218) were male (Figure 1), a pattern broadly consistent with the higher hospice-care needs typically observed among older women due to longer life expectancy and a greater burden of chronic conditions in later life. The age-group breakdown (Figure 2) shows that the largest cohort, 163 patients (33.5%), fell within the 75–84 years band, followed by 123 patients (25.2%) aged 85 and over, 110 patients (22.6%) aged 65–74, and 91 patients (18.7%) aged 25–64, confirming that the great majority of patients were in older age groups typical of palliative-care populations.

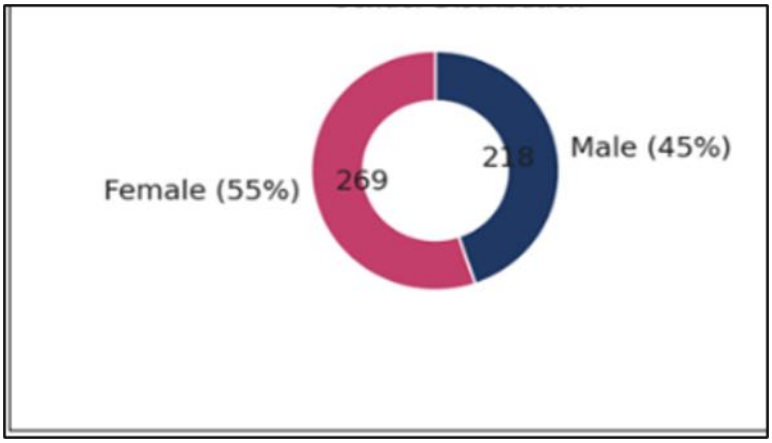

Figure 1 Patient Demographic Profile by gender distribution

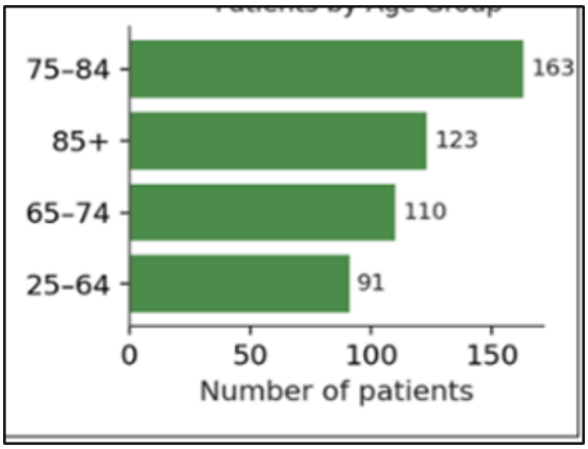

Figure 2 Patient Demographic Profile by age group (N=487)

New patient intake rose sharply over the period under study, from 4 patients in 2020 to 9 in 2021, 17 in 2022, 207 in 2023, and 264 in 2024 (Figure 3), an upward trend consistent with an ageing population and growing awareness of hospice services. This trend has direct implications for staffing and capacity planning, discussed further in Section 5.

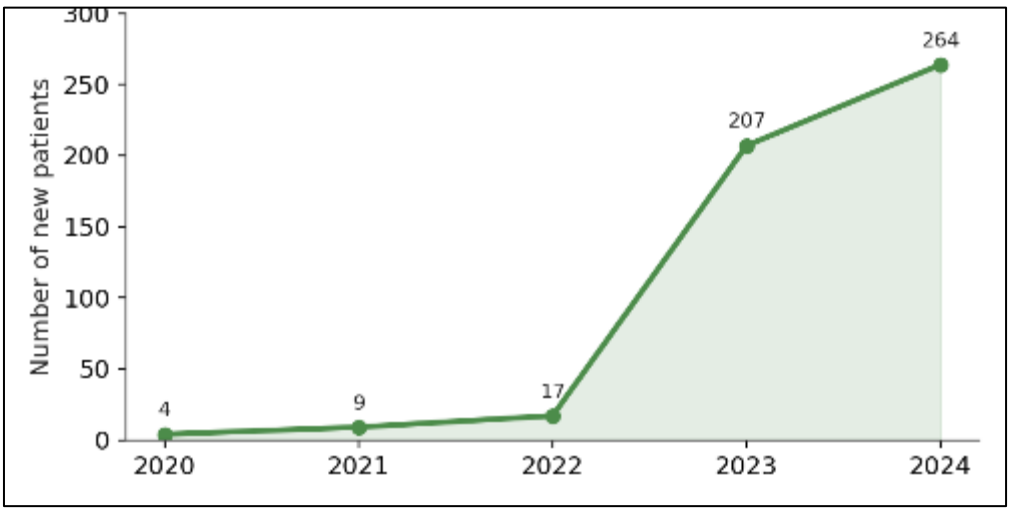

Figure 3 New Patients Entering care by year(2020-2024)

4.2. Diagnosis Profile and Length of Care

Cancer was diagnosed in 52% of patients (255), with the remaining 48% (233) presenting non-cancer terminal or chronic conditions, indicating a broadly balanced palliative-care caseload. The most common primary diagnosis groups were dementia, including Alzheimer's disease (81 cases), digestive-organ conditions (69 cases), other non-cancer diagnoses (65 cases), other cancer (54 cases), and respiratory and intrathoracic conditions (45 cases) (Figure 4).

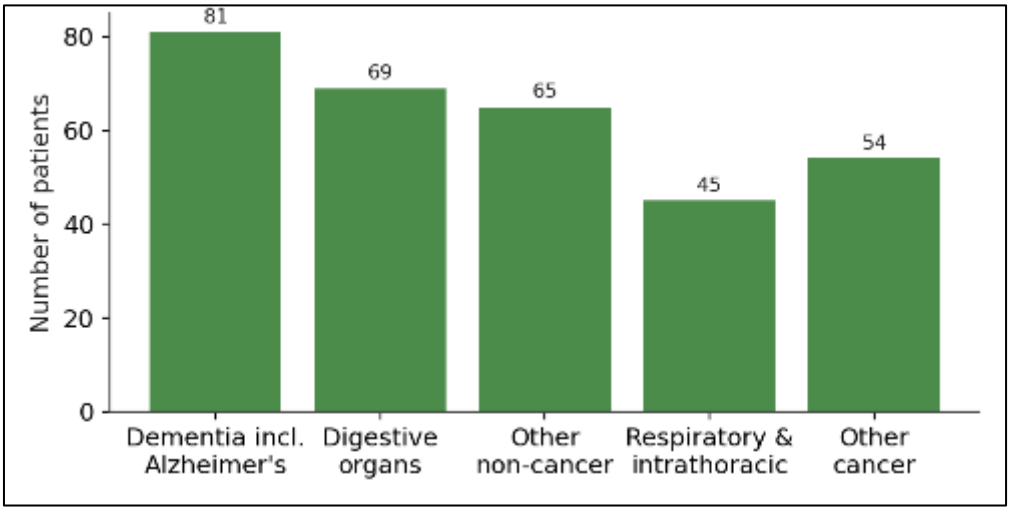

Figure 4 Top five primary diagnosis groups

The average length of care across all patients was 162 days (approximately 5.5 months). This varied considerably by age: the 25–64 years group had the longest average length of care at 211 days, consistent with the more prolonged trajectories typical of younger patients with terminal conditions, while the 85-and-over group had the shortest average length of care at 120 days, suggesting that older patients tend to enter hospice care at a more advanced stage of illness.

4.3. Patient Outcomes

The dashboard's Corrected Discharge Status and Patient Status measures classified 345 patients as alive and 164 as deceased, producing an overall mortality rate of 34%. Broken down by gender (Figure 5), 193 female and 152 male patients were classified as alive, while 90 female and 74 male patients were classified as deceased.

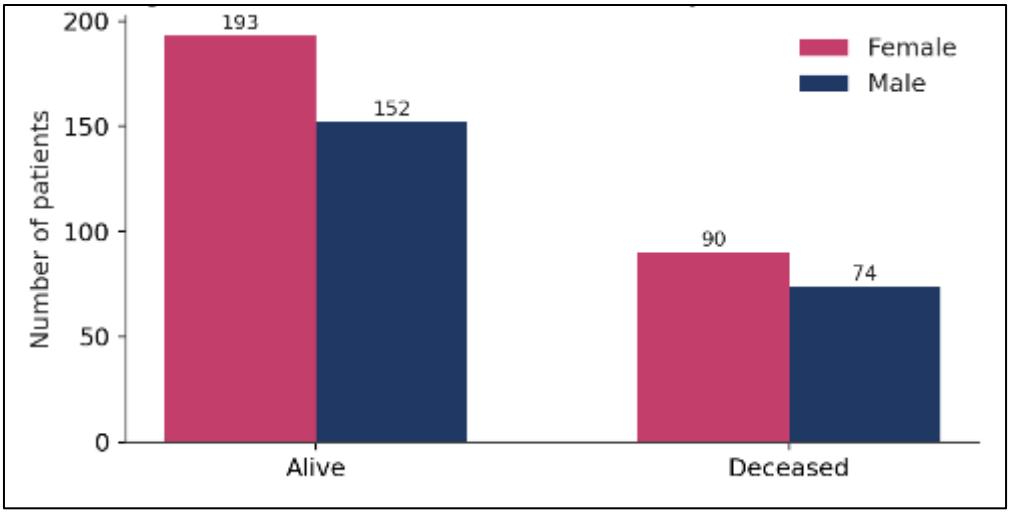

Figure 5 Patient status(Alive vs Deceased) by gender

Discharge-status analysis showed that 79 patients were discharged following death, 71 were discharged alive, 52 remained as continuing referrals, 24 had unused referrals, and 12 were discharged but not subsequently seen within three months (Table 3). Monthly discharge volumes were broadly stable across 2023 before rising sharply in early-to-

mid 2024, peaking at 106 discharges in April 2024, before falling to 47 in May and 27 in June 2024, a pattern that has direct implications for anticipating periods of elevated administrative and clinical workload.

Table 3 Distribution of discharge status categories (n = 238 discharge events)

Discharge status	Count	% of total
Discharged – died	79	33.2%
Discharged – alive	71	29.8%
Continuing referral	52	21.8%
Unused referral	24	10.1%
Discharged, not seen within 3 months	12	5.1%

4.4. Resource Allocation and Professional Workload

Attendance data indicated that 54.1% of recorded patient interactions were attended, 38.0% were marked 'Not Recorded', and 7.9% were categorised as 'Other', suggesting scope for improved attendance-recording practice. The Professional Workload visual showed marked variation in contact volume across healthcare professionals, with the highest-contact role (a chaplaincy/pastoral post, labelled 'Priest' in the source data) recording 190 contacts, compared with fewer than 20 contacts for the lowest-volume roles, indicating an uneven distribution of patient-facing workload across the professional team. A diagnosis-by-age-group heatmap further showed that dementia diagnoses were concentrated in the 75–84 years band, while digestive-organ conditions, which were also associated with the longest average lengths of stay, were prevalent across multiple age groups, information that can support more targeted staffing and bed-capacity planning.

4.5. Summary of Key Performance Indicators

Table 4 Summary of headline dashboard KPIs

KPI	Value	Interpretation
Total Patients	487	Unique patients under hospice care, 2020–2024
Total Visits	2,498	All recorded patient interactions
Average Length of Care	162 days	Ranges from 120 days (85+) to 211 days (25–64)
Mortality Rate	34%	Proportion of patients recorded as deceased
Cancer Prevalence	52%	Proportion of patients with a cancer diagnosis
New Patients in 2024	264	Compared with 4 in 2020 – a 66-fold increase
Attendance Rate	54.1%	Proportion of contacts marked as attended

5. Discussion

The findings demonstrate that a commodity business-intelligence platform can deliver meaningful decision support in a resource-constrained palliative care setting, directly addressing each of the study's four research objectives.

With respect to the first objective, the KPIs implemented, total patients, total visits, average length of care, mortality rate, and cancer prevalence, align closely with those identified as central to palliative-care monitoring in the literature (Stadler et al., 2016; Bowers et al., 2023; Tang et al., 2021). The steep rise in new patient intake, from 4 in 2020 to 264 in 2024, is a particularly consequential finding: it confirms, quantitatively, the demand pressure that motivated the project and provides administrators with a concrete evidence base for future staffing and funding decisions, addressing the fourth objective concerning funding-evidence needs.

On the second objective, integrating the CANISC and ICARE datasets into a single star-schema model, following the retain-rather-than-remove approach to duplicate contact records, preserved the granularity needed for visit-frequency and workload metrics while still enabling patient-level deduplication for headline counts. This mirrors the data-

integration challenges reported by Dowding et al. (2018) and demonstrates one practicable resolution: rather than treating all repeated patient identifiers as errors, the analyst must distinguish genuine duplication from legitimate repeated clinical contact.

Regarding the third objective, dashboard evaluation, the involvement of hospice administrators and stakeholders throughout design and testing is consistent with the user-centred design principles shown to improve usability and adoption by Martinez et al. (2018) and Gremyr et al. (2020). The resulting interactivity, cross-filtering by care source and date range, allowed stakeholders to move fluidly between organisation-wide KPIs and setting-specific detail, addressing the drill-down and customisation features identified as critical by Khairat et al. (2018) and Daley et al. (2013).

The variation in average length of care by age group, 211 days for patients aged 25–64 compared with 120 days for those aged 85 and over, has direct resource-planning implications: younger patients require sustained bed or caseload capacity over a longer horizon, while the frailty and later-stage presentation typical of the oldest patients concentrates resource demand into a shorter, more intensive period. Similarly, the marked concentration of dementia diagnoses in the 75–84 age band and the comparatively long stays associated with digestive-organ conditions provide a basis for the kind of targeted, diagnosis-aware staffing anticipated by Bowers et al. (2023).

The uneven distribution of professional contact volume, with one role recording an order of magnitude more contacts than others, echoes workload-imbalance concerns raised by Salehi et al. (2021) and points to a practical risk of burnout if left unaddressed; the dashboard's Professional Workload view makes this imbalance visible to managers in a way that manual reporting previously did not. At the same time, the substantial proportion of attendance records marked 'Not Recorded' (38%) illustrates a limitation common to routinely collected clinical data: the dashboard can only surface patterns that the underlying data-capture process reliably records, a constraint also noted by Dowding et al. (2018) and Budhwani et al. (2020) in relation to palliative and end-of-life care data quality more broadly.

Finally, the dashboard's descriptive rather than predictive character is consistent with the current state of the field: as Kamal et al. (2015) and Lim et al. (2022) observe, the integration of predictive analytics and machine learning into palliative-care dashboards remains comparatively underexplored, and this project's scope and timeframe did not permit such extension, a limitation addressed directly in Section 6.

6. Conclusion

This paper has presented the design, development, and evaluation of an interactive Power BI clinical dashboard for Hospice of the Valleys, developed using the CRISP-DM framework and grounded in the wider clinical-dashboard literature. Applied to 487 patients and 2,498 visits recorded between 2020 and 2024, the dashboard surfaced a substantial rise in patient intake, a near-balanced gender and cancer-diagnosis profile, an overall mortality rate of 34%, and clear variation in length of care and professional workload across patient subgroups. These findings directly answer the study's research question by demonstrating that a well-designed clinical dashboard can improve palliative care and resource management through real-time, interactive visibility into caseload, outcomes, and workload, insight that was previously obscured within manual, siloed reporting systems.

6.1. Limitations

Three limitations qualify these conclusions. First, incomplete source data, particularly missing contact dates, attendance flags, and ethnic-group information, constrained the depth of certain analyses and required conservative handling that may understate some metrics. Second, inherent inconsistencies between discharge-method and discharge-status fields required rule-based correction, introducing a residual risk of misclassification despite careful validation. Third, and most significantly, the dashboard remains descriptive: it reports what has happened rather than forecasting what is likely to happen, limiting its use for proactive, rather than reactive, resource planning.

6.2. Recommendations for Future Work

Building on these limitations, four directions are recommended. First, predictive analytics should be incorporated, using machine-learning models to forecast referral volumes, length of care, and mortality risk, extending the approach demonstrated by Bowers et al. (2023) into this setting. Second, data-capture practices should be strengthened for currently incomplete fields, including contact dates, ethnicity, and standardised diagnosis coding, to support more granular demographic and clinical analysis. Third, the KPI set should be broadened to include bed-occupancy rates and staff-satisfaction metrics, providing a fuller operational picture alongside patient-level outcomes. Fourth, real-time alerting should be added for conditions such as extended length of care or resource thresholds being exceeded, moving

the dashboard from a purely retrospective reporting tool toward the kind of proactive clinical decision support envisaged by Waitman et al. (2011) and Suraj et al. (2022).

Taken together, this work indicates that modestly resourced palliative-care providers can derive substantial decision-support value from widely available business-intelligence tools, provided that data governance, stakeholder engagement, and careful handling of clinically sensitive missing data are prioritised throughout development.

Compliance with ethical standards

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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