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Artificial Intelligence and Automation in Enterprise CRM Systems: A Systematic Review of Salesforce Governance, Operational Efficiency, And Customer Engagement in the Renewable Energy Sector

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ABSTRACT: Renewable energy enterprises manage long customer relationships that run from lead capture through permitting, construction, commissioning, billing, and service, and many now run them on cloud CRM platforms such as Salesforce that offer workflow automation and artificial intelligence. This systematic review, reported to PRISMA 2020, asks what peer-reviewed evidence exists on AI and automation in enterprise CRM, how it bears on governance, data security, operational efficiency, and customer engagement, and how far the evidence reaches renewable energy. Searches on 22 October 2026 identified 2,809 records (165 from 29 web queries and 2,644 from a supplementary collection of journal records); after screening and full-text assessment, 14 studies published between 2020 and 2026 were included and synthesised thematically. Only one study, a design study on an electricity marketing system in China, concerned an energy business, and none examined Salesforce Flow or a renewable energy developer. Eight of the 14 studies were rated low quality, and the quantified efficiency results came from synthetic or simulated data. Five themes emerged: efficiency gains that are mostly self-reported, engagement through prediction and personalisation, governance that is discussed more than tested, integration as the main scalability limit, and adoption barriers led by data quality and skills. The paper sets out a research agenda of eight priorities for secure and intelligent CRM in renewable energy enterprises.

KEYWORDS: customer relationship management, Salesforce, artificial intelligence, process automation, renewable energy, data governance, PRISMA 2020, thematic synthesis.

1. INTRODUCTION

A renewable energy enterprise sells and serves over a long period. A distributed solar developer, for example, wins a lead, qualifies it, contracts it, secures a permit and a utility interconnection agreement, builds the system, applies for permission to operate, bills the customer or the offtaker, and then services and renews the relationship for years. Each step creates records, tasks, documents, and messages that a customer relationship management (CRM) platform is expected to hold in one place. Customer relationship management is a strategic and information-driven process and not only a software product (Boulding et al., 2005), and recent reviews link it to firm innovation (Guerola-Navarro et al., 2021). Cloud platforms now add workflow automation and artificial intelligence (AI) to the CRM record, so that routing, data entry, scoring, drafting, and triage can be done by the platform and not by staff (Libai et al., 2020; Huang & Rust, 2021; Davenport et al., 2020; Rust & Huang, 2014).

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Salesforce is one of these platforms, and its documentation describes two automation layers that matter here. Flow Builder lets administrators build flows that automate business processes (Salesforce, n.d.-a), and Agentforce places AI agents on the platform, with an Einstein Trust Layer that provides grounding, data masking, toxicity detection, an audit trail, and zero data retention for model calls (Salesforce, n.d.-c; Salesforce, n.d.-b). These are vendor descriptions and not evidence of effect. Whether such tools raise efficiency, improve engagement, and stay within security and privacy duties has to be learned from independent studies, and the question is sharper in energy, where customer data include addresses, consumption, financial incentives, and interconnection files, and where AI systems fall under security and risk standards such as the NIST Cybersecurity Framework 2.0 (NIST, 2024), NIST SP 800-53 (Joint Task Force, 2020), and ISO/IEC 27001 (ISO/IEC, 2022).

Existing reviews cover parts of this ground. Saha et al. (2021) reviewed 138 papers on analytical CRM across business sectors, Singh et al. (2020) surveyed machine learning for CRM, and Hartanto et al. (2025) reviewed AI for CRM service effectiveness. None of these, to the knowledge of this review, centres on a renewable energy enterprise or on Salesforce governance. This paper therefore asks five questions. First, what AI-driven CRM automation has been studied in renewable energy and energy utility organisations? Second, what does the evidence say about Salesforce Flow, Einstein AI, predictive analytics, and customer engagement? Third, how are CRM governance, data security, and enterprise system integration treated? Fourth, what barriers to adoption, scalability, and operational efficiency are reported? Fifth, what research agenda follows for secure and intelligent CRM in renewable energy enterprises?

The review follows PRISMA 2020 (Page et al., 2021a; Page et al., 2021b) and synthesises findings thematically (Thomas & Harden, 2008; Braun & Clarke, 2006). Its contribution is an evidence-based map of what is and is not known, graded by study quality, and an explicit agenda. Section 2 sets out the methods, Section 3 gives the results, Section 4 discusses implications and limits, and Section 5 concludes.

2. METHODS

2.1 Protocol and reporting standard

The review was reported according to the PRISMA 2020 statement and its explanation and elaboration document (Page et al., 2021a; Page et al., 2021b), and its procedure follows the structured approach to literature reviews described for software and information systems research by Kitchenham and Charters (2007). The review protocol was not registered in advance. The review period was January 2015 to October 2026, chosen because cloud CRM platforms with embedded analytics became common in that interval, and the search was run on 22 October 2026. Screening and data extraction were carried out by one reviewer, and no second-reviewer agreement statistic is reported. Reasons for every exclusion were coded and are summarised in Figure 1.

2.2 Eligibility criteria

Table 1 lists the inclusion and exclusion criteria. A study had to be a peer-reviewed journal article or full conference paper in English, published between January 2015 and October 2026, that applied AI or automation inside a CRM or customer-facing enterprise platform and reported at least one outcome or issue in governance, security, privacy, or compliance; operational efficiency; customer engagement; systems integration; adoption barriers; or scalability. The criteria follow the population, intervention, and outcome logic recommended for review protocols (Kitchenham & Charters, 2007). Studies were classed as Tier A when set in renewable energy, solar, wind, energy utilities, or electricity retail, and as Tier B when set in any other sector. Peer review was accepted when the journal or proceedings is published by a recognised scholarly publisher or when the page states it, and a record was excluded under E2 when no such statement could be found on the page read.

Table 1. Eligibility criteria and exclusion codes.

Code	Criterion	Rule applied
IC1	Date	Published between January 2015 and October 2026
IC2	Publication type	Peer-reviewed journal article or full conference paper in English; blogs, vendor documentation, press releases, theses, preprints, and unpublished manuscripts excluded
IC3	Study design	Empirical study, design or model study, case study, or review; pure opinion pieces excluded
IC4	Technology	AI (machine learning, predictive analytics, generative AI, agents) or automation (workflow automation, robotic process automation, low-code, rule or flow automation) applied within a CRM or customer-facing enterprise platform such as Salesforce, Microsoft Dynamics 365, HubSpot, SAP, or Oracle
IC5	Outcome	At least one of: governance, security, privacy or compliance; operational efficiency; customer engagement or experience; systems integration; adoption barriers; scalability
Tier	Context	Tier A: renewable energy, solar, wind, energy utility, or electricity retail. Tier B: any other sector
E1 to E6	Exclusion codes	E1 date; E2 publication type or peer review not verifiable; E3 not CRM or customer-facing; E4 no AI or automation; E5 no eligible outcome; E6 not in English

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2.3 Information sources and search strategy

Two sources were searched, as Table 2 shows. The first was web search of scholarly records, using 29 queries on 22 October 2026 that combined CRM or Salesforce terms with AI or automation terms, outcome terms, and energy terms, for example "customer relationship management" AND "energy utility" AND "machine learning", and Salesforce AND governance AND (security OR "access control" OR compliance). Twenty-seven queries used the standard search mode and two the extended mode. The second source was a supplementary collection of journal records assembled from four reference-list documents, which held 2,644 entries and 1,160 distinct titles after deduplication by title. Two titles fell outside the date window, and the remaining 1,158 were screened by title on the same criteria as the web records; 27 were retained for retrieval, and none of them reached the included set (Section 3.17). The search strings, screening counts by source, and extraction matrix are given in Tables 9 to 13. No subscription citation database was searched. Background references used to interpret themes, such as the AI-CRM adoption studies of Chatterjee et al. (2020) (2020) and Chatterjee et al. (2021) (2021), were gathered outside the systematic search, were not screened or extracted, and are not counted as included studies.

Table 2. Information sources and search strategy.

Source	Scope and date	Strategy	Records
Web search of scholarly records	22 October 2026; 27 standard and 2 extended queries	Boolean strings combining CRM or Salesforce, AI or automation, outcome, and energy terms; all scholarly hits recorded	165
Supplementary collection of journal records	Four reference-list documents; entries dated up to 2026	Deduplication by title; date filter; title screening for CRM and customer-facing automation; 27 retained, 0 included	2,644 (1,160 distinct titles)
Background reading	Throughout drafting	Used for context and interpretation only; not screened, not extracted, not counted	Not counted

2.4 Selection, data extraction, and quality appraisal

Records were deduplicated by title and by digital object identifier. Stage 1 screened titles against IC1 to IC5. Stage 2 assessed the full text, or at least the full abstract, of retained records; a report whose page could not be read was recorded as not retrieved and was not included. For each included study the reviewer extracted authors, year, venue, country, sector and tier, design, CRM platform, AI or automation technique, and findings on governance, efficiency, engagement, integration, and barriers. Quality was appraised with the Mixed Methods Appraisal Tool (Hong et al., 2018) where its criteria applied, and otherwise with a three-level rating of high, moderate, or low, with the reason recorded. Extraction from the abstract alone was flagged and capped at a low rating.

2.5 Synthesis

Findings were synthesised by thematic synthesis, which codes findings line by line, groups codes into descriptive themes, and then generates analytical themes (Thomas & Harden, 2008), supported by the six-phase thematic analysis of Braun and Clarke (2006). Because the included studies are heterogeneous in design and measures, no meta-analysis was attempted, and effect sizes are reported only as the studies state them. The strength of evidence for each theme was graded as low, moderate, or high by the number of studies, their quality ratings, and whether outcomes were measured or only asserted. A theme resting on a single study, or on studies mostly rated low, could not be graded above low, and a theme was graded moderate only when at least two moderate or high quality studies agreed (Hong et al., 2018).

2.6 Review type, method choices, and confidence assessment

Literature reviews differ in purpose, and the choice of type shapes what can be claimed. A typology of literature reviews in information systems separates reviews by their contribution to knowledge development, from summarising to theory building (Schryen et al., 2020). This review is an evidence-mapping systematic review whose aim is to find out what has been tested, where, and how well. Guidance for standalone systematic reviews in information systems stresses a clear question, explicit inclusion criteria, and a transparent search (Okoli, 2015), and the guidance on evidence-informed management knowledge stresses that systematic review in management must cope with heterogeneous designs and with the need to synthesise qualitative and quantitative work together (Tranfield et al., 2003). Methodological guidance for literature reviews as a research method distinguishes systematic, semi-systematic, and integrative approaches (Snyder, 2019), and the foundational advice on writing a review stresses concept-centred synthesis rather than author-centred listing (Webster & Watson, 2002). A synthesis of the systematic literature review method in software engineering demonstrates the value of reporting search strings, selection rules, and quality criteria so that another team can repeat the work (Kitchenham et al., 2009). The book-length treatment of systematic approaches to literature reviews supplies the practical sequence from question to synthesis (Booth et al., 2016), and the original PRISMA statement, which preceded the 2020 update, set the principle of reporting a flow of records from identification to inclusion (Moher et al., 2009).

Confidence in each theme was assessed separately from the quality of individual studies. The GRADE-CERQual approach assesses confidence in findings from qualitative evidence synthesis through four components: methodological limitations, coherence, adequacy of data, and relevance to the review question (Lewin et al., 2018). For quantitative and mixed findings, the Cochrane handbook describes the logic of certainty assessment in terms of risk of bias, inconsistency, indirectness, imprecision, and reporting bias (Higgins et al., 2024). Here the CERQual components were applied to all five themes with one adaptation: relevance was judged against renewable energy enterprises and not against the broad question of CRM. The resulting

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judgements, reported in Section 3.16, are reviewer judgements made by a single reviewer and are offered as a transparent starting point and not as definitive ratings.

3. RESULTS

3.1 Study selection

The searches identified 2,809 records, of which 165 came from web search and 2,644 from the supplementary collection. Removing duplicates (15 and 1,484 respectively) left 1,310 records for title screening, and 1,224 were excluded: 1,196 as not CRM or customer-facing (E3), 16 for having no AI or automation (E4), 7 by publication type (E2), 3 for language (E6), and 2 by date (E1). Of the 86 reports sought, 51 could not be retrieved, because the page or full text could not be read. The remaining 35 were assessed in full and 21 were excluded: 9 as not CRM or customer-facing, 5 because peer review could not be verified from the page, 3 for having no AI or automation, 3 for lacking an eligible outcome, and 1 by date. Fourteen studies were included, one in Tier A and thirteen in Tier B. Figure 1 shows the flow.

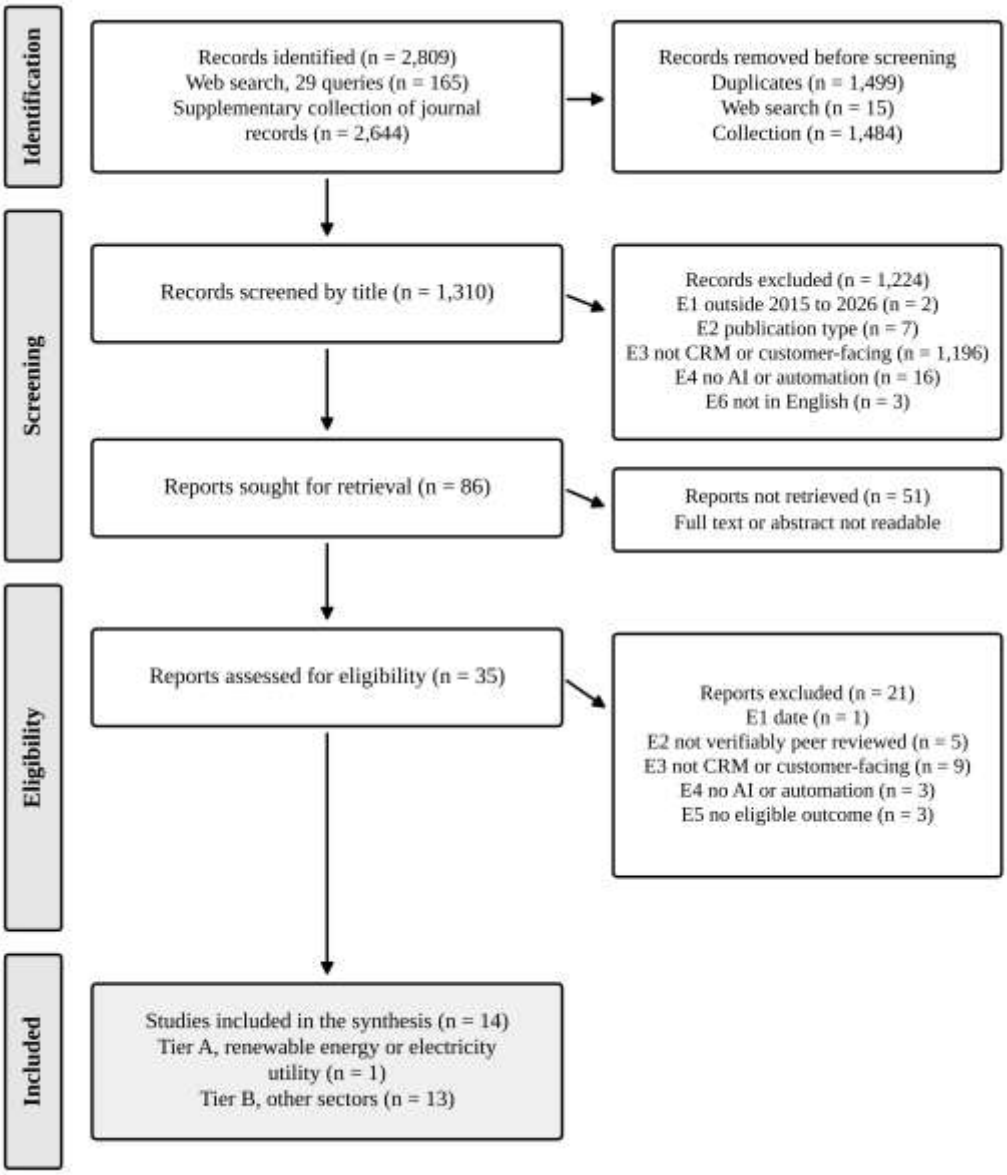


Figure 1. PRISMA 2020 flow diagram of record identification, screening, eligibility assessment, and inclusion.

Two exclusions at the full-text stage matter for the topic. Two Salesforce records on governance and security, a zero-trust access management design for Salesforce CRM and an anomaly-detection study on Salesforce transactional data, were excluded under E2 because the pages read did not state peer review, and would be the first candidates to reinstate if review is confirmed. A 2010 article on smart utilities and CRM was excluded under E1. Smart-meter and demand-response analytics papers were excluded as not CRM or customer-facing, which marks a boundary: analytics on meter data are not CRM unless they run inside a customer-facing platform (Wang et al., 2019).

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3.2 Characteristics of the included studies

Table 3 summarises the 14 included studies. They span 2020 to 2026, with seven published in 2025 and none before 2020 within the window. By design, four were reviews (Hokmabadi et al., 2025; Singh et al., 2020; Saha et al., 2021; Agarwal et al., 2025), three were mixed-methods or survey studies (Kumar et al., 2026; Pavlinic et al., 2026; Chatterjee et al., 2022), two were interview studies (Marcinkevage & Kumar, 2025; Khneyzer et al., 2024), four were design or model studies (Gupta, 2025; Ileana et al., 2025; Sebola et al., 2025; Chen & Ge, 2024), and one was a literature review combined with an assessment of Salesforce Einstein Analytics tools (Kumar, 2025). Only one study was set in an energy business (Chen & Ge, 2024). The others were cross-sector or set in higher education, retail banking, financial transactions, tourism, retail, healthcare, or banking.

Table 3. Characteristics, technique, and quality rating of the 14 included studies.

Study	Sector (tier)	Design	AI or automation technique	Quality
Singh et al. (2020)	E-commerce and telecommunications (B)	Survey review of machine learning for CRM	Supervised, unsupervised, and deep learning	Low
Saha et al. (2021)	Multiple, telecommunications focus (B)	Systematic review of 138 papers	Analytical CRM; supervised learning, clustering	Moderate
Chatterjee et al. (2022)	B2C organisations, India (B)	Survey, 326 usable responses, PLS-SEM	AI-integrated CRM	Moderate
Khneyzer et al. (2024)	Tourism, retail, healthcare, Lebanon (B)	Five interviews, thematic analysis	AI chatbots	Low
Chen and Ge (2024)	Electric power utility, China (A)	Design study with synthetic data and load tests	LSTM demand prediction; anomaly detection; CI/CD automation	Low
Hokmabadi et al. (2025)	SMEs and startups (B)	Mixed-methods review, Scopus based	AI agents, NLP, predictive analytics	Moderate
Marcinkevage and Kumar (2025)	Higher education, United States (B)	20 interviews, grounded theory	Generative AI for constituent CRM	Moderate
Kumar (2025)	Cross-sector (B)	Literature review and tool assessment	Salesforce Einstein Analytics, bots	Low
Gupta (2025)	Financial transactions (B)	Model study on a public dataset	Adaptive anomaly detection	Low
Ileana et al. (2025)	Not specified (B)	Design science with simulated traffic	Collaborative filtering; failover; RBAC	Low
Agarwal et al. (2025)	Subscription services (B)	PRISMA review and proposed model	Hybrid ensemble churn model	Low
Sebola et al. (2025)	Banking (B)	Prototype with two scenarios	Sentence-BERT, T5, reinforcement learning chatbot	Low
Kumar et al. (2026)	Cross-sector, India (B)	Interviews (37) and survey (356), SEM-ANN	Generative AI-enabled CRM	High
Pavlinic et al. (2026)	Retail banking, Croatia (B)	Survey (340) and three bank interviews	Predictive analytics, generative AI	Moderate

3.3 Quality of the evidence

One study was rated high (Kumar et al., 2026), five moderate (Hokmabadi et al., 2025; Marcinkevage & Kumar, 2025; Pavlinic et al., 2026; Saha et al., 2021; Chatterjee et al., 2022), and eight low. Four of the low ratings reflect extraction from the abstract alone because the full text was not readable (Singh et al., 2020; Kumar, 2025; Gupta, 2025; Agarwal et al., 2025). Two further low ratings reflect designs with no real customers or users: the IoT and CRM study ran simulated traffic of 10 to 10,000 requests on four server nodes (Ileana et al., 2025), and the electricity marketing study used synthesised data on 100,000 customer profiles (Chen & Ge, 2024). The chatbot prototype reported no quantitative results (Sebola et al., 2025), and the interview study of chatbots rested on five interviewees (Khneyzer et al., 2024). The sole Salesforce-specific study was written by a Salesforce employee,

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which carries a risk of vendor bias (Kumar, 2025). Quality ratings therefore limit how far any theme below can be trusted, and they are reported with each theme.

3.4 Theme 1: Automation and operational efficiency

Every included study that discusses automation expects it to cut repetitive work, but few measure it. Hokmabadi et al. (2025) report from the studies they reviewed that AI agents reduce time and cost, and that CRM reduces repetitive data entry, without a quantified result of their own. In the survey of retail banks, 74 of 87 AI adopters said AI reduced campaign design and launch time, and two banks said the reduction was partial (Pavlinic et al., 2026). In higher education, staff time savings were cited as potential and not measured, and one participant reported accuracy rising from 74 per cent to 90 per cent through model-to-model validation (Marcinkevage & Kumar, 2025). Interviewees on chatbots reported faster response and resolution and more inquiries handled without extra staff (Khneyzer et al., 2024). The only measured efficiency figures come from system tests on synthetic or simulated data: login response of 150 ms at low load and 450 ms at high load, a reported saving of $9{,}000amonthagainstatraditionaldeployment, anda22-monthbreak-evenona200{,}000$ migration in the electricity marketing study (Chen & Ge, 2024); and CPU use near 80 per cent beyond 5,000 requests in the IoT study (Ileana et al., 2025). Evidence for this theme is therefore broad in direction and thin in measurement, and robotic process automation and low-code literature offers the same pattern of expected benefit with limited field data (Syed et al., 2020; van der Aalst et al., 2018; Sanchis et al., 2020).

3.5 Theme 2: Predictive analytics, personalisation, and engagement

Engagement is the outcome most often claimed. Kumar et al. (2026) found that adoption of generative AI-enabled CRM predicted stakeholder engagement (beta 0.663, R-squared 0.44), and that functional value was the strongest predictor of trust (beta 0.897), but these are perceptions and not operational measures. Pavlinic et al. (2026) report one bank that recorded better engagement, lower unsubscribe rates, higher net promoter score, and fewer complaints, all self-reported. The reviews tie machine learning in CRM to customer identification, attraction, retention, and development (Singh et al., 2020; Saha et al., 2021), and a model study reports churn prediction with 82 per cent accuracy and 75 per cent F1 (Agarwal et al., 2025). Churn and lead models have a longer record than the generative tools: profit-driven churn modelling in telecommunications (Verbeke et al., 2012), ensemble churn models (Coussement & De Bock, 2013), and machine-learning lead scoring for business-to-business sales (Gonzalez-Flores et al., 2025). Related practitioner and conceptual work in the supplementary collection is consistent with this direction, covering CRM-based sales forecasting for multichannel lenders (Dada et al., 2021), machine learning for acquisition and retention and predictive lifecycle management (Ogundairo & Ayivi-Donkor, 2023), churn and lifecycle value in telecommunications (Oziri et al., 2020), customer service analytics (Sakyi et al., 2022), revenue assurance with AI (Sakyi et al., 2023), and AI in pharmaceutical customer engagement (Williams et al., 2025). These records reached the retrieval stage but could not be assessed in full, and they are described only as their titles indicate. Engagement evidence is therefore consistent but mostly attitudinal, and the single study to model utility customers is a demand and anomaly design and not an engagement study (Chen & Ge, 2024).

3.6 Theme 3: Governance, data security, and privacy

Governance is discussed more than it is tested. The Scopus-based review of SMEs recommends prioritising data security, flags the burden of the General Data Protection Regulation for small firms, and lists OAuth-based and compliance tooling without a formal governance framework (Hokmabadi et al., 2025). Higher education interviewees named privacy regulation as a constraint and called for protection of models from tampering, input sanitisation, bias detection, and human oversight (Marcinkevage & Kumar, 2025). In retail banking, 20 per cent of non-adopting financial respondents cited privacy and compliance as a barrier, and the authors recommend governance, privacy by design, and bias testing under the GDPR, the EU AI Act (European Parliament and Council, 2024), and the Digital Operational Resilience Act (Pavlinic et al., 2026). The few security controls that were actually tested come from design studies: penetration testing with no successful SQL injection or cross-site scripting violations in the electricity marketing system (Chen & Ge, 2024), role-based access control and encryption in the IoT and CRM design (Ileana et al., 2025), and an adaptive anomaly detector with 99.6 per cent accuracy and 79.8 per cent precision on a public credit card dataset (Gupta, 2025). Yet no included study tested least privilege, audit completeness, or agent permissions inside a CRM platform. Wider governance sources set the expectations: data governance as a decision-rights framework (Khatri & Brown, 2010; Abraham et al., 2019), organisational AI governance (Mantymaki et al., 2022), the NIST AI Risk Management Framework (Tabassi, 2023), and zero trust architecture (Rose et al., 2020).

3.7 Theme 4: Integration and scalability

Integration is the clearest scalability constraint. The review of SMEs warns of an "integration illusion" in which disconnected SaaS tools look integrated and are not, and it recommends an API-first stack (Hokmabadi et al., 2025). Higher education data were fragmented, siloed, and often on premises, and generative AI was described as expensive at scale by one participant (Marcinkevage & Kumar, 2025). In the survey of managers at 17 organisations, system characteristics affected system fit (0.19) and organisational fit (0.23), and system fit had the strongest effect on implementation (0.32) (Chatterjee et al., 2022). The electricity marketing study scaled transaction throughput from 30 to 90 per second as instances went from one to four, found database reads to be the bottleneck, and used REST and gRPC interfaces with an API gateway and incremental rollout (Chen & Ge, 2024). The IoT study saw response time rise about 12 per cent and CPU about 8 per cent beyond 50 ms of simulated latency (Ileana et al., 2025). Salesforce-oriented practice work in the supplementary collection addresses ETL and data integration in Salesforce-centric architectures (Badmus et al., 2019a) and MuleSoft integration patterns in multi-cloud Salesforce architectures (Badmus et al., 2022b), and it was not assessable in full.

3.8 Theme 5: Barriers to adoption

Data quality and skills lead the barriers. Poor data quality was the most frequent barrier among higher education participants, ahead of security and privacy risk, uncertain return on investment, shifting costs, and staff trust (Marcinkevage & Kumar, 2025). Among non-adopting banks, lack of in-house expertise (26 per cent), privacy and compliance concerns (20 per cent), and data quality (16 per cent) led (Pavlinic et al., 2026). Information barriers (beta 0.696) and norm barriers (0.409) predicted inertia, inertia reduced adoption, and management support moderated that link (Kumar et al.,

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2026). Technology turbulence affected both acceptance and failure paths of AI-integrated CRM, and inappropriate implementation drove failure (Chatterjee et al., 2022). Adoption literature in the supplementary collection reaches similar points, with AI adoption readiness in small and medium enterprises (Alieme et al., 2023), the role of the business analyst in AI transformation (Alieme et al., 2025), determinants of scaling AI and automation from pilot (Dawud, 2026b), the adoption gap in supply chain AI (Ogundairo & Ayivi-Donkor, 2024), digital transformation of operations (Agboada et al., 2018), and automation and analytics in pharmaceutical manufacturing (Obukadata et al., 2021). Related CRM-specific records in the collection address enterprise CRM adoption and revenue analytics in financial services (Okoli et al., 2025), and CRM and workflow automation in small healthcare practices (Eyetsemitan et al., 2024). Table 4 summarises the five themes, the included studies that support each, and the strength of evidence.

Table 4. Thematic synthesis: themes, supporting studies, and strength of evidence.

Theme	Principal finding	Supporting included studies	Evidence strength
1. Automation and efficiency	Time and cost savings are expected and mostly self-reported; measured figures come from synthetic or simulated tests	(Hokmabadi et al., 2025; Pavlinic et al., 2026; Marcinkevage & Kumar, 2025; Khneyzer et al., 2024; Chen & Ge, 2024; Ileana et al., 2025)	Low
2. Prediction and engagement	Engagement is linked to personalisation and prediction, but outcomes are perceptions	(Kumar et al., 2026; Pavlinic et al., 2026; Singh et al., 2020; Saha et al., 2021; Agarwal et al., 2025)	Low to moderate
3. Governance and security	Frameworks are recommended; few controls are tested	(Hokmabadi et al., 2025; Marcinkevage & Kumar, 2025; Pavlinic et al., 2026; Chen & Ge, 2024; Ileana et al., 2025; Gupta, 2025)	Low
4. Integration and scalability	Integration and data access, not compute, limit scale	(Hokmabadi et al., 2025; Marcinkevage & Kumar, 2025; Chatterjee et al., 2022; Chen & Ge, 2024; Ileana et al., 2025)	Low to moderate
5. Barriers	Data quality, skills, and inertia lead; management support moderates	(Marcinkevage & Kumar, 2025; Pavlinic et al., 2026; Kumar et al., 2026; Chatterjee et al., 2022)	Moderate

3.9 Salesforce Flow, Einstein, and Agentforce

The included evidence on Salesforce itself is a single abstract-level study that reviews literature and assesses Einstein Analytics tools and bots, reporting a favourable influence of AI in CRM without figures (Kumar, 2025). No eligible peer-reviewed study of Salesforce Flow was retrieved, so the account here rests on platform documentation for what Flow and Einstein do (Salesforce, n.d.-a; Salesforce, n.d.-c) and on the vendor account of how the trust layer masks data before a model call (Salesforce, n.d.-b; Chandler-Garcia, 2023). A comparative study of automation tools and frameworks on the Salesforce platform shows that performance can be compared in a controlled way (Ciechan, 2023), but it lies outside the systematic search. Practice-oriented work in the supplementary collection covers the Salesforce delivery stack, namely continuous integration and delivery pipelines (Badmus et al., 2018), DevOps tooling with Copado, Flosum, and Salesforce DX (Badmus et al., 2020), and Git-based version control and code review (Badmus et al., 2022a). It also covers governance, with a five-pillar framework for Salesforce platform management in regulated healthcare covering data architecture, identity and access, integration, change and release, and compliance monitoring (Badmus et al., 2019b), a privacy-by-design role-based security architecture for sensitive personal data (Badmus et al., 2024), and a governance framework for AI-assisted CRM workflows, Agentforce deployment, risk, and organisational readiness (Badmus et al., 2025), as well as nonprofit CRM transformation on Salesforce NPSP and NPC (Badmus et al., 2026). Marketing automation research in the same collection adds explainable architectures (Sanni et al., 2026), adaptive control in financial compliance environments (Sanni et al., 2022), lifecycle-aware automation with federated learning (Sanni et al., 2023), and process mining for auditable lifecycle control (Sanni et al., 2025). These records were not assessed in full. They indicate where practitioner attention sits, which is delivery discipline and governance, and they show that the peer-reviewed evidence base for Flow and Agentforce has yet to be built.

3.10 Evidence from renewable energy and energy utilities

Renewable energy enters the review through one included study and a body of context. The included study is the electricity marketing information system of the State Grid Hebei Electric Power Marketing Service Center, which combined a CRM module with billing, account management, and customer service on a cloud-native architecture, used an LSTM with attention for demand prediction (reported 5 per cent better accuracy than a baseline LSTM), and an isolation forest and autoencoder ensemble for anomaly detection (Chen & Ge, 2024). It used synthesised data and no commercial CRM product, so it is a design study and not evidence of field performance. The wider energy literature explains why customer engagement matters in the

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sector: smart energy services create value co-creation and engagement (Goncalves & Patricio, 2022), smart grid customer engagement draws on marketing initiatives (Senyapar et al., 2024), prosumer-era market design changes the customer role (Parag & Sovacool, 2016), and residential solar adoption is shaped by barriers, uncertainty, and peer effects (Rai et al., 2016; Palm, 2017; Schelly, 2014). Operations literature in the supplementary collection covers preventive maintenance programme design in renewable energy systems (Yeboah et al., 2024), safety and environmental compliance programmes for renewable projects (Yeboah et al., 2025), lessons from large-scale solar projects (Yeboah & Ike, 2020), and the economic, environmental, and social effects of large-scale renewable integration (Joseph & Uzondu, 2024). It also covers community trust as a measurable variable (Komi, 2024), interpretable failure prediction for distributed renewable assets (Komi & Adamolekun, 2021), AI-powered digital twins for renewable systems (Shittu & Shittu, 2024), and smart grid architectures for high renewable penetration (Adenuga, 2022). For utilities, work on automation, analytics, and customer-centric innovation in utility and service operations (Nnabueze et al., 2023b) and on service delivery with automation and risk reduction (Sakyi et al., 2024) is closest to CRM, and a model for customer experience from workforce behaviour and operational data (Akhigbe et al., 2023) is related. None of these ties a CRM platform to a renewable energy developer's lifecycle from lead to commissioning.

3.11 Research agenda

Table 5 turns the gaps into eight priorities. The agenda draws on the themes above and on the evidence reviews of (Saha et al., 2021; Hokmabadi et al., 2025). They are ordered by how directly they close the distance between the evidence found and the questions asked. The first two address the absence of any study of a renewable energy developer on a commercial CRM platform and of Salesforce Flow. The next three address governance, security, and data quality, where claims outrun tests. The last three address integration and scalability, customer engagement measured as behaviour, and adoption in energy organisations. Each priority names the minimum design that would count as evidence, so that later studies can be compared on the same footing.

Table 5. Research agenda for secure and intelligent CRM in renewable energy enterprises.

No.	Priority	Question	Minimum design
1	Field evidence in renewable energy	What do Flow automation and AI decision support change in a distributed solar or storage developer, from lead to commissioning?	Controlled before and after study or staggered rollout with operational data
2	Salesforce Flow and Einstein	What are the effects, failure modes, and limits of Flow and Einstein features on processing time and data accuracy?	Platform benchmarks and case studies with reproducible configurations
3	Access control for agents	Does least-privilege, task-scoped access for AI agents reduce exposure and incidents?	Permission-utilisation measures and red-team tests in sandbox orgs
4	Auditability	How complete is the audit trail when automation and agents act on records?	Trace completeness ratio against a reference task set
5	Data quality controls	Which validation, deduplication, and reconciliation controls protect accuracy in automated workflows?	Sampled record audits with stated margins and defect bounds
6	Integration resilience	How do retry, buffering, and circuit-breaker designs affect availability with permitting, interconnection, and billing systems?	Fault-injection experiments and outage logs
7	Engagement as behaviour	Do prediction and personalisation change conversion, response time, and retention measured in transactions?	A/B tests with behavioural outcomes
8	Adoption in energy organisations	Which skills, ownership, and management support factors predict sustained use?	Longitudinal mixed methods across energy firms

3.12 Automation technologies in CRM and the platform evidence

The automation tools that enterprises place around a CRM fall into four classes, and the evidence differs by class. Robotic process automation (RPA) uses software robots to mimic user actions on existing interfaces. A systematic mapping of the scientific and industrial literature identified 54 primary studies and 14 commercial RPA tools and found that the analysis phase, in which candidate processes are selected, is poorly supported by existing methods (González Enríquez et al., 2020). These sources describe RPA as an adjacent technology to CRM and they do not test it inside a CRM platform. The second class is platform-native automation, which on Salesforce includes Apex code, Visualforce pages, and declarative or point-and-click tools such as Flow. A performance analysis of methods for building applications on the Salesforce platform compared approaches that use Apex, Visualforce, and no-code point-and-click builds (Miącz, 2019). It is the only peer-reviewed technical comparison found for the platform, and its scope is page performance and not governance or business outcomes. The third class is predictive and analytical automation, whose evidence base is the largest. A classification of 87 articles on data mining in CRM mapped techniques to CRM dimensions of customer identification, attraction, retention, and development (Ngai et al., 2009), and its taxonomy remains a standard reference for what analytical CRM covers. The fourth class is conversational

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automation. A randomised online experiment found that anthropomorphic cues raised users' compliance with chatbot requests (Adam et al., 2021), and a conceptual paper on service robots in the frontline proposed an acceptance model and an ethics agenda (Wirtz et al., 2018).

These technology classes sit inside a CRM strategy. A strategic framework for CRM links customer strategy, value creation, and information management as the components of a successful programme (Payne & Frow, 2005), and a theory of customer engagement behaviour defines engagement as behaviours beyond purchase, with antecedents and consequences at the level of customer, firm, and context (van Doorn et al., 2010). Both support the position of this review that automation should be evaluated against the outcome that the CRM exists to serve, and not only against processing time. Table 6 summarises the technology classes, the evidence found, and the main gap in each.

Table 6. Automation technology classes in CRM, representative evidence, and the main gap.

Class	Representative evidence	What the evidence shows	Main gap
Robotic process automation	(Hofmann et al., 2020; González Enríquez et al., 2020; Lacity & Willcocks, 2016)	Four traits of RPA; 54 studies and 14 tools mapped; one operator case	No test inside a CRM platform; process selection poorly supported
Platform-native automation (Apex, Visualforce, Flow)	(Miącz, 2019)	Performance comparison of build methods on one platform	No governance or business outcome tests; none for Flow
Predictive and analytical automation	(Ngai et al., 2009; Singh et al., 2020; Saha et al., 2021)	Large classifications and reviews of data mining and machine learning in CRM	Mostly cross-sector; few field evaluations of effect
Conversational automation	(Adam et al., 2021; Wirtz et al., 2018; Khneyzer et al., 2024)	Experimental effect on compliance; acceptance model; interview study	Outcomes are attitudes and compliance, not operational results

3.13 Customer analytics in energy outside CRM platforms

A wider body of peer-reviewed work studies energy customers with analytics that could feed a CRM, although it was not set inside a CRM platform and therefore did not meet the inclusion criteria. It is described here to show what the sector knows and to mark the boundary between customer analytics and CRM automation. This literature was gathered outside the systematic search and is not part of the 14 included studies.

Segmentation is the most common use. Churn prediction in the energy sector has been studied with eight models applied to about 81,800 residential electricity customers (Vezzoli et al., 2020). For solar, a fact sheet from the National Renewable Energy Laboratory describes the use of machine learning and data analysis to reduce the cost of acquiring residential solar customers (Duran, 2017).

Engagement and trust are the second theme. A review of customer management tools in the energy industry examined CRM tools for energy companies in deregulated markets (Asimakopoulou et al., 2011), which is the closest sector precedent to the question posed here, though it predates cloud AI platforms by more than a decade.

Privacy is the third theme, and it matters for governance. Energy consumption data can reveal household routines, so a CRM that links such data to named customers inherits these privacy concerns. Table 7 lists the context studies with their setting, method, and relevance to a CRM in a renewable energy enterprise.

Table 7. Energy customer analytics studies outside CRM platforms and their relevance to CRM automation.

Study	Setting and method	Relevance to renewable energy CRM
(Tureczek & Nielsen, 2017)	Structured review of smart meter classification, 34 papers	Segmentation methods that could feed CRM scoring
(Rhodes et al., 2014)	Clustering of 103 homes in Austin linked to survey data	Link between usage clusters and customer attributes
(Fernandes et al., 2017)	Clustering of about 1,000 gas consumers	Segmentation from smart metering
(Vezzoli et al., 2020)	Eight churn models on about 81,800 electricity customers	Churn prediction in the energy sector
(Duran, 2017)	NREL fact sheet on analytics for residential solar customer acquisition	Lead and acquisition analytics for solar developers
(Parrish et al., 2020)	Systematic review of demand response engagement	Trust and perceived risk as engagement drivers

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Study	Setting and method	Relevance to renewable energy CRM
(Asimakopoulou et al., 2011)	Review of CRM tools for energy companies in deregulated markets	Closest sector precedent for CRM in energy
(Lee & Hess, 2021)	Comparison of smart meter privacy policy in six jurisdictions	Privacy duties for customer energy data

3.14 Security and governance of energy sector information systems

The supplementary collection contains a body of work on the security of electric utility and critical infrastructure systems, and it informs how CRM governance should be framed for energy enterprises. A systematic review of the security of operational technology networks in electric utilities addresses NERC CIP compliance and architectural threat mitigation (Adegbite et al., 2020), a security architecture model addresses IT and OT convergence in regulated energy networks (Adegbite et al., 2022), and a vulnerability governance architecture is proposed for power and utilities corporations (Adegbite et al., 2024a). An AI-driven security operations architecture for utility sector security operations centres (Adegbite et al., 2024b) and a zero trust architecture for operational technology in North American critical infrastructure (Ahmed et al., 2021) extend the theme. These sources are cited for the topics their titles state. They show that governance for energy enterprises is usually framed as segmentation, vulnerability management, and monitoring, and they suggest the control questions that a renewable energy CRM should answer: which systems the CRM may reach, which identities it may use, and how its actions are monitored.

No included study applied these ideas to a CRM. The gap is practical as well as scholarly, because renewable energy developers increasingly link customer systems to monitoring platforms, billing, and field service tools, and each link extends the segment that governance must cover. The research agenda in Table 5 therefore includes controls for agent access and integration resilience as priorities.

3.15 Project delivery, finance, and operations context in renewable energy

Customer relationships in renewable energy are tied to project delivery and finance, which shapes what a CRM must track. Project management strategies for solar energy deployments in emerging markets (Amayo et al., 2024) and in West Africa (Amayo et al., 2025) stress scheduling, stakeholder engagement, and risk control, all of which generate customer-facing events. Data-driven portfolio optimisation for utility-scale solar, wind, and battery storage (Ilesanmi et al., 2024) and revenue optimisation in energy distribution through integrated financial planning and analytics (Nnabueze et al., 2024) show how analytics already inform finance in the sector. Business model work on sustainable large-scale service organisations with predictive analytics (Nnabueze et al., 2023a) and digital supply chain governance in energy and infrastructure (Okonkwo et al., 2024) connect customer operations to the wider enterprise. Automated ESG reporting in energy projects using blockchain-driven smart compliance management (Abioye et al., 2023) and predictive maintenance and condition monitoring in critical power and energy infrastructure (Adaramola et al., 2018) show the compliance and operational data that a customer system may need to reference. These sources were not assessed against the inclusion criteria and are cited as context for the sector.

The common message is that a renewable energy enterprise has long, multi-party customer journeys with regulatory milestones, and the CRM is the place where status, documents, and communications meet. That is the setting in which the automation and governance themes of this review would have to be tested.

3.16 Confidence in the review findings

Table 8 reports a CERQual-style assessment of confidence in each theme (Lewin et al., 2018). The assessment draws on the quality ratings of Section 3.3 and on the relevance of the evidence to renewable energy enterprises, and it is a single reviewer's judgement. Confidence is low or very low for four of five themes, which follows from the small number of included studies, the prevalence of low quality ratings, and the near absence of energy sector evidence. The barriers theme reaches moderate confidence because three moderate or high quality studies converge on data quality, skills, and inertia, although none was set in renewable energy (Kumar et al., 2026; Pavlinic et al., 2026; Marcinkevage & Kumar, 2025). Confidence would rise if the two excluded Salesforce governance studies were confirmed as peer reviewed and extracted, but even then no energy study would be added.

Table 8. Confidence in the thematic findings, assessed with CERQual-style components (single-reviewer judgement).

Theme	Methodological limitations	Coherence	Adequacy	Relevance to renewable energy	Overall confidence
1. Automation and efficiency	Serious	Moderate concern	Thin	Indirect	Low
2. Prediction and engagement	Moderate	Good	Moderate	Indirect	Low
3. Governance and security	Serious	Good	Thin	Indirect	Very low
4. Integration and scalability	Serious	Good	Thin	Partly direct (one energy study)	Low
5. Barriers to adoption	Moderate	Good	Adequate	Indirect	Moderate

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3.17 Search record, screening decisions, and extraction matrix

This section reproduces within the manuscript the records needed to repeat or audit the selection. Table 9 lists the 29 web queries exactly as submitted on 22 October 2026, with the search mode and the number of scholarly records each returned. Table 10 gives the screening decisions by source and stage, Table 11 the reports that could not be retrieved, Table 12 the supplementary records that were sought, and Table 13 the extraction matrix for the 14 included studies. The records are given here and not in a separate file so that the paper can be assessed as a single document (Page et al., 2021a).

Table 9. Web search strings as submitted, with search mode and scholarly records returned (total 165).

No.	Query string	Mode	Scholarly records
1	'CRM' AND 'artificial intelligence' AND 'renewable energy'	Standard	1
2	'customer relationship management' AND solar	Standard	0
3	'customer relationship management' AND 'energy utility' AND 'machine learning'	Standard	4
4	Salesforce AND 'Einstein' AND (study OR evaluation OR case)	Standard	1
5	Salesforce AND Flow AND automation AND (workflow OR 'process automation')	Standard	0
6	Salesforce AND governance AND (security OR 'access control' OR compliance)	Standard	0
7	'CRM' AND 'predictive analytics' AND 'customer engagement'	Standard	1
8	'CRM' AND 'generative AI' OR 'AI agents' AND enterprise	Standard	10
9	'CRM' AND 'data quality' AND (integration OR migration)	Standard	10
10	'CRM adoption' AND barriers AND (SME OR enterprise)	Standard	10
11	'robotic process automation' AND CRM	Standard	10
12	'low-code' AND CRM OR Salesforce	Standard	10
13	'customer engagement' AND 'renewable energy' AND digital platform	Standard	0
14	'lead management' OR 'lead scoring' AND solar installers	Standard	0
15	'digital transformation' AND 'energy sector' AND CRM	Standard	3
16	'CRM' AND 'API integration' AND ERP AND scalability	Standard	3
17	'CRM' AND 'data privacy' AND 'GDPR' AND AI	Standard	2
18	smart meter OR 'customer data' AND utility AND 'customer engagement' AND machine learning	Standard	10
19	'CRM' AND 'operational efficiency' AND automation AND case study	Standard	7
20	'CRM' AND 'customer lifecycle' AND 'machine learning'	Standard	7
21	Salesforce Einstein artificial intelligence CRM empirical study	Standard	10
22	Salesforce governance security access control compliance CRM study	Standard	8
23	CRM energy utility customer churn machine learning electricity retail journal article	Extended	9
24	solar PV installer customer relationship management software lead conversion study	Extended	0
25	Microsoft Dynamics 365 OR HubSpot artificial intelligence CRM automation empirical	Standard	10
26	utilities CRM customer experience artificial intelligence energy suppliers digital customer engagement	Standard	9
27	chatbot OR 'virtual assistant' electricity utility customer service CRM integration journal	Standard	10
28	renewable energy company customer relationship management system implementation case study sales automation	Standard	10
29	electricity retailer customer data platform AI personalization customer engagement energy retail	Standard	10

Table 10 shows that the supplementary collection contributed no included study. Its 2,644 entries reduced to 1,160 distinct titles, 2 of which fell outside the date window, and title screening retained 27 for retrieval; the other 1,131 were judged not to concern CRM or customer-facing systems. Of the 27, four could be read at abstract level and all four were excluded, two because peer review could not be verified (E2), one as not CRM or customer-facing (E3), and one for lacking AI or automation (E4). The other 23 could not be located. The 14 included studies therefore all came from web search, and the collection's value to the review is as context, not as evidence.

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Table 10. Screening decisions by source and stage.

Stage	Web search	Supplementary collection	Total
Records identified	165	2,644	2,809
Duplicates removed	15	1,484	1,499
Records screened by title	150	1,160	1,310
Excluded at title stage	91	1,133	1,224
E1 date	0	2	2
E2 publication type	7	0	7
E3 not CRM or customer-facing	65	1,131	1,196
E4 no AI or automation	16	0	16
E6 language	3	0	3
Reports sought	59	27	86
Reports not retrieved	28	23	51
Reports assessed in full	31	4	35
Excluded at full-text stage	17	4	21
E1 date	1	0	1
E2 peer review not verifiable	3	2	5
E3 not CRM or customer-facing	8	1	9
E4 no AI or automation	2	1	3
E5 no eligible outcome	3	0	3
Studies included	14	0	14

Table 11 classifies the 51 reports that could not be retrieved, and the effect on selection can be judged from it. Half of the 28 web reports (14) were on one publisher whose pages the fetch tool is not allowed to read, so the retrieved set is tilted toward publishers whose pages were open, mainly MDPI and Springer. The unretrieved titles include six that concern Salesforce, among them a Salesforce governance and access management roadmap and a study of managed-package security, and three that concern energy customers: analytics for customer behaviour in the energy and utility industry, CRM in the energy sector, and customer engagement in retail electricity markets. These three could have been Tier A studies. The direction of the bias is therefore against the review's own topic, and it probably understates both the Salesforce and the energy evidence. The finding that one included study concerns an energy business should be read as a lower bound on what exists and not as a measure of absence (Page et al., 2021a).

Table 11. Reports that could not be retrieved, by source and reason.

Source	Reports	Reason
sciencedirect.com	14	Fetch blocked by the publisher (robots exclusion)
researchgate.net	5	Client error on fetch
tandfonline.com	3	Client error on fetch
onlinelibrary.wiley.com	2	Client error on fetch
reference-global.com	1	Unreadable binary content
researcher.ibm.com	1	Page showed a publication list, not the article
ieeexplore.ieee.org	1	Empty content
pmc.ncbi.nlm.nih.gov	1	Interstitial verification page
Supplementary collection	23	No page found by title search

Table 12 lists the 27 supplementary records that were sought. Their titles show why the collection yielded nothing: most concern Salesforce engineering and administration, marketing automation, or customer analytics, and three concern predictive maintenance or failure prediction in distribution

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equipment, which are operational analytics and not CRM. The table also shows how few could be read. Supplementary records are identified by author and year only, because they are not part of the evidence base of this review.

Table 12. Supplementary records sought for retrieval and their outcome.

First author (year)	Title (shortened)	Outcome
Badmus (2025)	A governance framework for AI-assisted CRM workflows: Agentforce ...	Not retrieved
Badmus (2020)	A comparative framework for Salesforce DevOps tooling: Evaluating ...	Not retrieved
Badmus (2018)	A systematic review of CI/CD pipeline strategies in Salesforce ...	Not retrieved
Badmus (2019)	A conceptual model for ETL design and data integration in ...	Not retrieved
Badmus (2019)	A governance framework for Salesforce platform management in ...	Read; excluded (E4)
Badmus (2024)	A privacy-by-design framework for role-based security architecture ...	Not retrieved
Badmus (2022)	A framework for Git-based version control and code review governance ...	Not retrieved
Badmus (2022)	A systematic review of MuleSoft ESB integration patterns in ...	Not retrieved
Badmus (2026)	A framework for nonprofit CRM transformation using Salesforce NPSP ...	Not retrieved
Dada (2021)	Designing CRM-based sales forecasting models for multichannel ...	Read; excluded (E2)
Eyetsemitan (2024)	CRM and workflow automation in small healthcare practices: A process ...	Not retrieved
Okoli (2025)	Enterprise CRM technology adoption and revenue growth analytics in ...	Not retrieved
Ogundairo (2023)	Machine learning approaches to customer acquisition and retention: A ...	Read; excluded (E2)
Oziri (2020)	Predictive analytics applications in reducing customer churn and ...	Not retrieved
Nnabueze (2023)	Transforming utility and service operations through automation, ...	Not retrieved
Sakyi (2022)	Customer service analytics as a strategic driver of revenue growth ...	Not retrieved
Sakyi (2023)	Revenue assurance strategies leveraging artificial intelligence and ...	Not retrieved
Sakyi (2024)	Digital transformation in service delivery leveraging automation and ...	Not retrieved
Akhigbe (2023)	A conceptual model for improving customer experience using workforce ...	Not retrieved
Sanni (2022)	Adaptive control models for AI-driven marketing automation in ...	Not retrieved
Sanni (2023)	Lifecycle-aware marketing automation using federated learning for ...	Not retrieved
Sanni (2025)	Problem-oriented process mining for auditable marketing automation ...	Not retrieved
Sanni (2026)	Designing explainable AI based marketing automation architectures ...	Not retrieved
Williams (2025)	Artificial intelligence in pharmaceutical commercialization: ...	Read; excluded (E3)
Yeboah (2024)	Program design for advanced preventive maintenance in renewable ...	Not retrieved
Komi (2021)	Interpretable machine learning for early failure prediction in ...	Not retrieved
Shittu (2024)	AI powered digital twins for predictive maintenance and operational ...	Not retrieved

Table 13 is the extraction matrix. For each included study it records the country or region, sector, design, CRM platform, technique, and the quality rating assigned in Section 3.3, and the findings by theme are reported in Sections 3.4 to 3.8. Entries are shortened from the extraction forms, which held the full text of each field, and a blank or generic platform entry means that the page read did not name a platform.

Table 13. Extraction matrix for the 14 included studies.

Study	Country or region	Sector	Design	CRM platform	Technique	Quality
Hokmabadi et al. (2025)	Not stated on the page read	SMEs and startups, cross-sector	Review: mixed-methods systematic literature review ...	Salesforce, HubSpot, Zoho CRM, Pipedrive	AI agents, machine learning, NLP, predictive ...	Moderate

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Study	Country or region	Sector	Design	CRM platform	Technique	Quality
Marcinkevage and Kumar (2025)	United States	Higher education	Qualitative grounded theory: semi-structured ...	Vendors named include Salesforce, ...	Generative AI: text analysis and synthesis	Moderate
Kumar et al. (2026)	India	Cross-sector: IT 28.09%, financial ...	Mixed methods: grounded-theory interviews	Generative AI-enabled CRM systems in general	Generative AI-enabled CRM	High
Pavlinic et al. (2026)	Croatia	Retail banking	Mixed methods: cross-sectional survey	Not named on the page read	Predictive analytics	Moderate
Singh et al. (2020)	Not stated on the page read	E-commerce and telecommunications ...	Review	Generic CRM	Supervised	Low
Saha et al. (2021)	International literature	Multiple sectors with ...	Systematic literature review of 138 papers	Generic analytical CRM	Supervised learning	Moderate
Kumar (2025)	Not stated	Cross-sector / not specified	Literature review plus assessment of Salesforce ...	Salesforce Einstein Analytics	AI-powered CRM, predictive analytics and bots	Low
Chatterjee et al. (2022)	India	B2C organisations	Cross-sectional survey analysed with PLS-SEM	Not named for sampled organisations	AI-integrated CRM systems	Moderate
Gupta (2025)	United States	Financial transactions / credit card ...	Design/model study with quantitative evaluation on a ...	Not named	Multivariate normal distribution model of ...	Low
Ileana et al. (2025)	Romania and Bulgaria	Not specified	Design science research with experimental	HubSpot CRM	Collaborative filtering for personalisation	Low
Khneyzer et al. (2024)	Lebanon	Tourism, retail and healthcare	Qualitative exploratory interview study	Not named	AI chatbots based on NLP and machine learning	Low
Agarwal et al. (2025)	Not stated on the page read	Online subscription service for the ...	Systematic literature review	Generic CRM/ERP systems	Hybrid ensemble supervised machine learning	Low
Sebola et al. (2025)	South Africa	Banking	Design/model study: prototype chatbot with described ...	Not a named CRM	Sentence-BERT matching against a knowledge ...	Low
Chen and Ge (2024)	China	Electric power utility, electricity ...	Design and model study with experimental evaluation	Custom electricity marketing information ...	LSTM with attention for power demand prediction	Low

The web search tool differs from a bibliographic database in ways that limit reproducibility: it returns no abstracts at the title stage, its ranking is not fixed, and publisher access varies by day. A search of Scopus, Web of Science, IEEE Xplore, and the ACM Digital Library was not possible in this work. The strings of Table 9 can be translated for such a database as TITLE-ABS-KEY(('customer relationship management' OR CRM OR Salesforce) AND ('artificial intelligence' OR 'machine learning' OR automation OR chatbot OR 'generative AI') AND (energy OR 'renewable energy' OR solar OR wind OR utility OR electricity)) with a second string that replaces the energy block by governance, security, or compliance terms, limited to 2015 to 2026. This string has not been run, and the review's claims are therefore bounded by the web search described here (Page et al., 2021a).

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4. DISCUSSION

4.1 Principal findings

The first finding is an absence. After 2,809 records and a full-text assessment of 35, one included study concerned an energy business, and it was a design study with synthetic data (Chen & Ge, 2024). No study examined Salesforce Flow, and the one Salesforce-specific study was abstract-level and written by a vendor employee (Kumar, 2025). The practical consequence is that a renewable energy enterprise adopting Flow and Agentforce does so on vendor documentation and cross-sector evidence, not on tested results for its own industry (Salesforce, n.d.-a; Salesforce, n.d.-c). The second finding is a pattern: the direction of evidence is consistent across sectors, with automation expected to reduce effort, prediction to improve engagement, and integration and data quality to limit scale, but measurement is weak and attitudinal outcomes dominate (Kumar et al., 2026; Pavlinic et al., 2026; Marcinkevage & Kumar, 2025). The third finding is that governance receives recommendation and little testing. This matters because the NIST and ISO frameworks make control effectiveness the object of assurance (NIST, 2024; Joint Task Force, 2020; ISO/IEC, 2022).

4.2 Implications for renewable energy enterprises

Three implications follow for an enterprise such as a distributed solar developer. First, treat vendor features as hypotheses and measure them on the enterprise's own work, using the six indicators of administrative time, workflow completion, data accuracy, policy compliance, availability, and response time, because the literature offers no benchmark. Second, give governance the same design attention as automation: least-privilege access, validation rules, audit trails, and approval gates for high-risk actions, in line with the zero trust model (Rose et al., 2020) and the AI risk framework (Tabassi, 2023). Third, plan integration deliberately, since the evidence names integration and data quality as the limits that compute does not remove (Hokmabadi et al., 2025; Chen & Ge, 2024; Chatterjee et al., 2022). The companion model paper to this review develops and tests such a design on synthetic organisational data, so that the effect of each component can be measured and bounded before field deployment.

4.3 Limitations

The review has limits that bear on its conclusions. No subscription citation database was searched, so relevant studies may have been missed, and the web search returned no abstracts at the title stage. Many publisher pages could not be read, which produced 51 unretrieved reports and tilted the retrieved set toward publishers whose pages were readable. One reviewer screened and extracted, with no agreement statistic. Four extractions rest on abstracts, and the quality ratings of eight studies are low. Extraction figures were taken from page text and not rechecked against the original PDFs. Peer review was inferred from publisher and venue for several conference papers (Gupta, 2025; Agarwal et al., 2025; Kumar, 2025; Sebola et al., 2025). The supplementary collection reached 1,160 distinct titles but only a small number could be read, so related work in it is described only as titles indicate. The protocol was not registered. Finally, evidence in this area moves quickly, and studies published after 22 October 2026 are not covered.

The evidence in this review has three different statuses, and they should not be read as one. Conceptual proposals state what a system could do and carry no test. Synthetic demonstrations, such as the design study of the electricity marketing system (Chen & Ge, 2024), show that a design works on generated data and load tests. Validated operational outcomes report results measured in running organisations, and the review found few of these and none in a renewable energy enterprise. Where the text reports an effect, the study type is stated, and the confidence ratings of Table 8 already reflect the weight each type can carry (Lewin et al., 2018).

4.4 Implications for research design

The review suggests five design principles for future studies. First, studies should report the operational outcome in units that a manager can use, such as minutes per record, completion rate, defect rate, and response time, and they should state the denominator. Second, field designs such as staggered rollouts or matched comparisons should replace purely attitudinal surveys when a firm introduces automation, since a staggered rollout can support causal estimates at modest cost. Third, governance studies should test controls and not only recommend them. Fourth, studies of Salesforce or other commercial platforms should publish configurations in enough detail to be repeated (Miącz, 2019). Fifth, energy sector studies should be sampled from renewable energy developers and utilities, with customer analytics linked to the CRM process they serve (Asimakopoulou et al., 2011; Duran, 2017).

Reporting standards would also help. Studies of AI in CRM often give accuracy without the base rate, or give satisfaction without the response rate, and the review found that several reported results only as perceptions. A minimal reporting set would cover the platform and version, the AI features and their configuration, the data volume, the outcome measures with their definitions, the comparison group, and the data sources, in line with the transparency expected of systematic evidence (Moher et al., 2009; Kitchenham et al., 2009).

4.5 A practitioner checklist derived from the evidence

Practitioners need guidance that can be used before the research agenda is completed. Table 14 turns the themes into a checklist of questions that a renewable energy enterprise can ask when it adopts or expands AI and automation in its CRM. The checklist is derived from the included studies and from the sector context, and it should be treated as a prompt for local measurement and not as a validated instrument. Each row pairs a question with the evidence that would answer it, so that an enterprise can build its own evidence base while the literature matures. The questions are written for a team that administers a platform such as Salesforce, and they can be asked at three points: before adoption, to set a baseline; after rollout, to compare against it; and at each review cycle, to detect drift. Teams that already track indicators for data quality and system performance can reuse them, and the appraisal logic of the mixed methods tool used in this review (Hong et al., 2018) can be applied to their own internal evaluations to judge whether a result is robust enough to act on.

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Table 14. Checklist of questions for adopting AI and automation in a renewable energy CRM.

Theme	Question to answer before and after adoption	Evidence to collect
Automation and efficiency	Which processes are automated, and what was the baseline processing time?	Minutes per record before and after; share of items handled without staff
Prediction and engagement	Does the model change decisions, and are outcomes measured in transactions?	Conversion, response time, and retention by cohort
Governance and security	Which identities and permissions do the automations hold?	Permission inventory; audit completeness; access review results
Integration and scalability	What happens during outages and at peak load?	API limit usage; buffer performance; incident logs
Barriers	Who owns the data and the automations, and are the skills in place?	Named owners; training records; data quality indicators

4.6 Position relative to earlier reviews

Earlier reviews of AI in CRM have mapped techniques across sectors and have concluded that the field is growing and that applications are broad (Singh et al., 2020; Saha et al., 2021; Hokmabadi et al., 2025). This review adds three things. It applies a structured eligibility screen and reports what fell away, which shows how few studies meet a modest bar for peer review and platform relevance. It grades confidence by theme, which shows that breadth of coverage does not translate into confidence. And it places the question in renewable energy, which earlier reviews did not do. The finding that no study examined Salesforce Flow or a renewable energy developer is itself a contribution, since it identifies the evidence that the sector still needs and the practice literature that cannot substitute for it (Payne & Frow, 2005; van Doorn et al., 2010).

4.7 Adjacent modelling work cited for context

Two groups of adjacent work frame how the included studies could be extended. A review of econometric and conceptual models for early technology adoption in emerging and transitional economies compares logistic growth, Bass diffusion, discrete choice, and machine-learning forecasting across sectors that include renewable energy systems (Oteri & Chibwaye, 2022). Those models suit the question of how quickly renewable energy developers adopt CRM automation, a question the included studies do not answer. A review of change management analytics for large system transitions covers readiness measurement and adoption trajectories (Oteri & Chibwaye, 2025), and it supplies measures that an adoption study of CRM automation could use. A predictive maintenance model developed for a cassava pulveriser illustrates the maintenance modelling approach that energy asset operators apply to equipment failure data (Oluleye & Ekun, 2022), and it is cited here for its modelling approach, not as a CRM study. None of these sources met the inclusion criteria, so they are not counted in the review.

A review of behavioural health data for policy innovation is cited for three principles that bear on the research gaps identified here. It reports that community-generated data adds context that makes interventions more relevant and accurate (Akinyelure, 2025), which parallels the missing customer-side evidence in the included CRM studies. It finds that advanced analytics can support real-time risk forecasting, intervention prioritisation, and resource optimisation when combined with other data sources (Akinyelure, 2025), which is the claim that most included studies make for CRM automation without independent testing. It also argues that closing the loop between data and decision-making needs ethical data governance and institutional capacity (Akinyelure, 2025). The source is a health policy review and was not part of the systematic search.

Two peer-reviewed studies of predictive modelling in health show the same methods applied to a different domain. An equitable machine-learning framework for chronic disease prediction in underserved communities Azigi and Abdulkareem (2024) and an approach that combines geospatial analytics with predictive modelling for early chronic-disease surveillance (Azigi et al., 2024) both concern predictive analytics on segmented populations, which parallels the customer segmentation and prediction tasks reviewed here. They concern health outcomes and not CRM, so they are cited for the modelling approach only and not as evidence on CRM platforms.

Reviews of data orchestration and workflow automation (Ogeawuchi et al., 2022a) and of data pipeline automation (Ogeawuchi et al., 2022b) describe the automation of data movement that sits behind CRM analytics. A practitioner study of cybersecurity strategies for safeguarding energy infrastructure (Ajayi et al., 2025) addresses the sector risks that energy customer systems share. None of them evaluates a CRM platform, so they are cited for context only.

Three further sources give context for automation and digital readiness. A systematic review of AI driven enterprise data analytics frameworks for decision intelligence (Iwuanyanwu et al., 2025b) and a review of AI based data analytics pipelines for large scale systems (Iwuanyanwu et al., 2025a) describe the analytics layer that CRM automation feeds, a study of artificial intelligence, robotics, and automation adoption in supply chain and fulfilment operations identifies determinants of moving from pilot to scale (Dawud, 2026a), and a study of construction SMEs examines the determinants of digital transformation readiness and their link to organisational performance (Ajayi et al., 2026). None of them evaluates a CRM platform, so they are cited for context only.

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5. CONCLUSION

Artificial intelligence and automation are being built into enterprise CRM platforms faster than the evidence about them is being gathered. The 14 studies that met the criteria point the same way across sectors: automation is expected to cut administrative effort, prediction and personalisation to raise engagement, and integration, data quality, and skills to decide whether either works at scale. The same studies are mostly low in quality, rely on self-reported or synthetic results, and test governance rarely. No study examined Salesforce Flow or a renewable energy developer on a commercial CRM platform, so the questions that matter most to renewable energy enterprises are open. The research agenda of eight priorities offers a way to close them, beginning with field studies in renewable energy and controlled tests of access control, auditability, data quality, and integration resilience. Until such evidence exists, renewable energy enterprises are best served by treating platform features as hypotheses to be measured against defined indicators and by building governance into automation from the start.

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