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A Web-Based Expert System Using Forward Chaining for Identifying Engine Power Loss Problems in the BMW 3 Series E36

Muhammad Ihsan Fawzi[*1], Ipung Permadi[2], Nur Chasanah[3], Emha Diambang Ramadhany[4], Azis Amirulbahar[5], Puteri Awaliatush Shofro[6]

[1,2,3,4,5,6]Informatics, Faculty of Engineering, Universitas Jenderal Soedirman, Indonesia

Email: [1]ihsfwz@incomso.com

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Abstract

The BMW 3 Series with production code E36, built between 1991 and 1998, remains widely owned in Indonesia, yet its age of more than two decades makes power loss a frequent complaint. Although the E36 engine is partially computerized, owners living far from an authorized or specialist workshop equipped with a diagnostic scanner cannot easily determine the cause of the power loss they experience. This study builds a web-based expert system, “Si Pak-E”, that identifies power loss problems on the BMW 3 Series E36 engine and recommends solutions. Knowledge was acquired through structured interviews with a BMW specialist mechanic and represented as a knowledge base of 22 problems, 33 symptoms, 22 solutions, and 22 production rules derived from a 33 × 22 decision table. Forward chaining was selected as the inference engine because diagnosis proceeds from observed symptoms toward a conclusion, while the waterfall model guided development. The system was implemented in PHP, MySQL, and Bootstrap with three user roles. Evaluation combined functional black-box testing with knowledge-base verification against the expert. Black-box testing executed 95 scenarios across 36 test cases and three roles, and all 95 (100%) produced the expected output. Rule-coverage verification traced all 22 production rules as consultation cases, and the system returned the problem and solution expected by the expert in 22 of 22 cases (100% agreement). The findings show that forward chaining is effective for symptom-driven automotive fault identification and that the system is a practical, transparent, and accessible diagnostic aid for E36 owners. Keywords: BMW E36, expert system, fault diagnosis, forward chaining, power loss, web-based.

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1. INTRODUCTION

The BMW 3 Series, popularly known as the “Seri 3”, with production code E36 was produced from 1991 to 1998 and remains one of the most owned and sought-after BMW variants in Indonesia. Based on the combined membership databases of three Indonesian BMW owner communities, namely BUCKS, E36 Indonesia, and E36 Owners Community, recorded during the knowledge-acquisition stage of this study, the registered population of E36 owners exceeds three hundred and is spread across the country, not counting owners who are not registered in any community [1], [2]. Because the engine and electronic systems of the E36 are already computerized, owners can in principle detect certain faults more easily than on fully mechanical cars. Nevertheless, the E36 is now more than two decades old, and as a vehicle marketed for its driving pleasure and large engine performance, the experience is severely disrupted when the car suffers from power loss, a condition in which the engine loses its expected power output and that can occur at any time.

The computerized nature of the E36 only helps when a diagnostic scanner is available. In practice, many owners live or are domiciled in areas that are not served by an authorized BMW workshop or by a

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specialist workshop that owns the appropriate scanner. Without access to such facilities, these owners are unable to determine what is actually wrong with their car and which corrective action should be taken. The problem therefore is twofold: how can an E36 owner identify and resolve a power loss problem without direct access to an expert, and how should a system be designed and built so that the diagnostic expertise of a specialist mechanic can be made available to owners anywhere.

An expert system offers a suitable answer to this problem. An expert system is an artificial-intelligence program that combines a knowledge base with an inference mechanism in order to emulate the decision-making ability of a human expert, allowing a user to solve a problem in a specific domain without the direct presence of that expert [3]. Such systems have become a mature technology for diagnostic tasks because they can store, reuse, and disseminate scarce expertise, thereby improving the productivity and consistency of decision-making [4]. Rule-based expert systems rely on two principal reasoning strategies: forward chaining, which is data-driven and reasons from known facts toward a conclusion, and backward chaining, which is goal-driven and works backward from a hypothesis [5], [6]. Because diagnosis typically begins from observed symptoms and proceeds toward an underlying cause, forward chaining is especially appropriate for diagnostic systems, and it can also be combined with backward chaining when bidirectional reasoning is required [7].

Fault diagnosis is itself a critical research area, since undetected faults in machines and equipment can lead to costly and unexpected failures, and a broad spectrum of artificial-intelligence techniques has been surveyed for this purpose [8], [9], including a recent review of artificial-intelligence-driven vehicle fault diagnosis for automotive maintenance [10]. Within the automotive domain in particular, rule-based and knowledge-based expert systems have proven effective for vehicle fault diagnosis. Mostafa et al. proposed an agent-based inference engine for an automated car failure diagnosis assistance system and reported that it reliably diagnosed most given car failure cases [11], while an earlier engine fault diagnosis expert system was developed to assist mechanics with a systematic, step-by-step analysis of failure symptoms [12], more recently, a knowledge-base approach combined with a decision tree has been applied to vehicle engine fault diagnosis [13]. More recent work has applied forward chaining to motorcycle damage diagnosis on a mobile platform [14] and to the diagnosis of three-wheeled motorcycle engine faults using a knowledge-based intelligent system [15], and to damage diagnosis of electric vehicles on a web platform [16]. These studies confirm the relevance of rule-based reasoning for vehicle diagnosis. To the best of our knowledge, however, no prior expert system targets power-loss diagnosis specific to the BMW 3 Series E36 engine family, whose symptom set, component-level granularity, and corrective procedures are particular to that engine family and are typically held only by experienced specialist mechanics. This is the gap that the present study addresses.

Beyond the automotive field, the forward chaining method has been applied successfully across a wide range of diagnostic domains, which demonstrates its maturity and generality. In healthcare, it has supported the diagnosis of, among others, the nursing process [17], dengue hemorrhagic fever [18], lung disease [19], cough-related illnesses [20], pregnancy disorders [21], and COVID-19 [22]. In agriculture and livestock, it has been used to diagnose diseases of rubber [23], tomato [24], and chili plants [25], as well as buffalo diseases [26], and systematic reviews confirm its popularity for plant and pest diagnosis [27]. It has likewise been applied to technical fault diagnosis of computers and smartphones [28]. Several of these works further combine forward chaining with uncertainty-handling techniques such as the certainty factor or Bayesian probability when symptoms are not fully certain [29], although for clearly observable symptoms, a deterministic rule base remains sufficient and keeps the reasoning transparent.

Beyond accessibility, an expert system also serves as a means of preserving expert knowledge. The expertise required to diagnose power loss on an ageing engine such as the E36 is accumulated over many years of hands-on practice and is held by only a small number of specialist mechanics. Such tacit knowledge

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is at risk of being lost when an expert retires or becomes unavailable, and it is difficult to transfer through conventional documentation alone. By eliciting this knowledge and structuring it as an explicit set of symptoms, problems, solutions, and rules, the proposed system both captures the expertise in a durable form and increases the productivity of the diagnostic process. This dual role of knowledge preservation and knowledge dissemination further motivates the present study.

The objective of this research is therefore to design and build a web-based expert system, named “Si Pak-E”, that identifies power loss problems on the BMW 3 Series E36 engine using the forward chaining inference method, and that recommends the appropriate solution for each identified problem. The system encodes the knowledge of a BMW specialist mechanic so that registered E36 owners, including those who are far from any specialist workshop, can carry out a guided self-diagnosis by entering the symptoms they observe and receiving the most probable problem together with its explanation and solution. The remainder of this paper describes the research method, including the design of the testing and evaluation procedure, presents the knowledge representation, system design, implementation, and evaluation results, discusses the findings in relation to prior work, and concludes with the contributions and directions for future development.

2. METHOD

This research produced a web-based expert system through a sequence of clearly defined stages. The reasoning of the system is governed by the forward chaining inference method, while the overall construction of the software follows the waterfall system-development model. This section formulates the problem to be solved, describes the data and tools used, and explains the proposed method, including knowledge acquisition, knowledge representation, the inference mechanism, and the development stages.

2.1. Research Data and Tools

The data used in this research are the data of power loss problems on the BMW 3 Series E36 engine, comprising the problem name, the symptoms associated with each problem, an explanation of each problem, and the recommended solution. These data were obtained directly from a domain expert and supported by several references. The development environment used a laptop with an Intel Core i7 processor and 12 GB of RAM as the main hardware, together with a smartphone camera and voice recorder used during data collection. The software tools included a code editor, the XAMPP package providing the Apache web server and the MySQL database, a modern web browser, and design tools for producing the user-interface mockups and diagrams.

2.2. Data Collection and Knowledge Acquisition

Two data-collection techniques were employed. The first was an interview, conducted intensively with the expert, namely a mechanic at a BMW specialist workshop who has handled BMW problems for many years, to acquire knowledge about power loss problems, their observable symptoms, and their solutions, and to elicit the functional requirements of the system. A complementary interview was conducted with a BMW E36 owner in order to capture the user-side requirements of the system. The second technique was a literature study, in which theoretical material and references relevant to expert systems, the forward chaining method, and the BMW E36 engine were examined. The acquired knowledge was then engineered into a machine-processable form and stored in the knowledge base as a set of facts and production rules. Figure 1 illustrates the general architecture of the expert system, which separates the development environment, where the expert’s knowledge is acquired and stored, from the consultation environment, where the inference engine applies that knowledge to the symptoms entered by the user.

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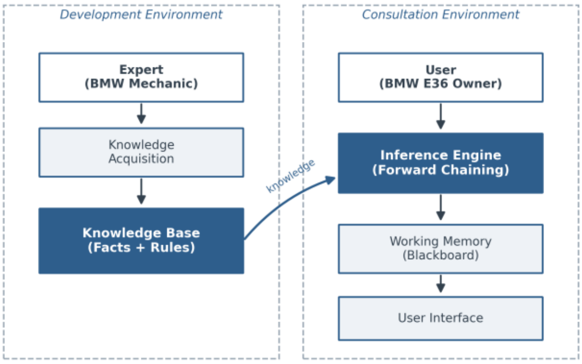

Figure 1. Architecture of the “Si Pak-E” expert system

During knowledge acquisition, particular attention was paid to ensuring that every symptom could be observed by an ordinary owner without specialised equipment. For this reason, the diagnostic procedure was structured so that the owner is guided through a sequence of simple checks, such as listening to the engine note, observing the RPM gauge under defined conditions, inspecting hoses for visible damage, and performing reversible cleaning steps with carburetor cleaner. Where a fault could affect any of several identical components, for example the spark plugs or ignition coils of the six combustion chambers, the knowledge base distinguishes each component individually so that the system can pinpoint the exact unit at fault rather than reporting only a general category. This level of granularity reflects the way the expert reasons in practice and is essential for producing an actionable solution.

2.3. Forward Chaining Inference Method

Forward chaining is a reasoning strategy of the inference engine that starts from a set of known facts and moves toward a conclusion [4], [6]. The technique matches the available facts against the IF part of each IF–THEN production rule; whenever the condition of a rule is satisfied, the rule is fired and its THEN part is asserted as a new fact in working memory. The process repeats until a goal, in this case a specific power loss problem, is reached. In the proposed system the facts are the symptoms selected by the user, and each rule links a combination of symptoms to a single problem and its solution. A production rule therefore has the general form expressed in Equation (1).

$$IF\ G^i \wedge G^j \wedge \ldots \wedge G^k\ THEN\ P^m \rightarrow S^n \quad (1)$$

where G^i, G^j, …, G^k are the symptoms that constitute the premise, P^m is the identified problem, and S^n is the recommended solution.

2.4. System Development Stages

The system was developed using the waterfall model, in which each stage is completed before the next one begins, as shown in Figure 2. The first stage, requirements analysis, used the interviews with the expert and prospective owners to acquire the domain knowledge and to determine the functional needs of the system. The second stage, system design, produced the data flow diagrams, the entity relationship diagram, the database design, and the user-interface mockups. The third stage, implementation, translated the design into program code. The fourth stage, testing, examined every process individually using both valid and invalid data to confirm correct behaviour. The final stage, maintenance, keeps the system running optimally and accommodates future improvements.

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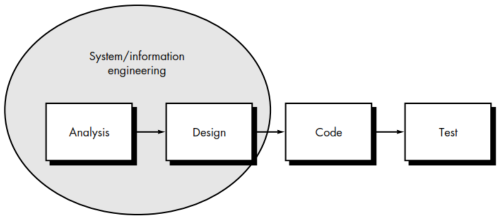

Figure 2. Waterfall development stages of the system [30]

3. RESULT

This section presents the knowledge representation that forms the core of the expert system, the rule base together with a worked inference example, the system design, the implementation, and the results of system testing. The expert system produced by this research is named "Si Pak-E" and is accessed through a web browser by three categories of user: the administrator, the expert, and the registered BMW E36 owner.

3.1. Knowledge Representation

The knowledge representation is the result of collecting and structuring the data of power loss problems on the BMW 3 Series E36. It consists of problem data, symptom data, solution data, and rule data. In total, the knowledge base contains 22 problems, 33 symptoms, and 22 solutions. The scale of the knowledge base is summarized in Table 1.

Table 1. Scale of the knowledge base

Knowledge component	Count	Identifier range
Problems	22	P01 – P22
Symptoms	33	G01 – G33
Solutions	22	S01 – S22
Rules	22	one rule per problem

The problems range from common, low-severity faults such as a dirty idle control valve to component failures such as damaged spark plugs, damaged ignition coils, a weak fuel pump, a clogged fuel filter, a leaking fuel hose, and throttle-related faults. Table 2 lists a representative subset of the problem data together with their identifiers, while Table 3 lists representative solution data. The complete catalogue of 22 problems and 22 solutions is stored in the knowledge base and managed by the expert through the system.

Table 2. Representative problem data

ID	Problem name
P01	Idle control valve (ICV) / idle up dirty
P02	Idle control valve (ICV) / idle up damaged
P03	Air flow / airmass hose dirty
P04	Air flow / airmass hose damaged
P05	Air flow / airmass damaged
P06	Spark plug of combustion chamber no. 1 damaged
P12	Ignition coil of combustion chamber no. 1 damaged
P18	Fuel pump weak
P19	Fuel filter dirty
P20	Fuel hose leaking
P21	Throttle valve dirty
P22	Throttle switch damaged

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Table 3. Representative solution data

ID	Solution
S01	Clean the idle control valve using carburetor cleaner
S02	Clean the air flow / airmass hose using carburetor cleaner
S03	Clean the fuel filter using carburetor cleaner
S04	Clean the throttle valve using carburetor cleaner
S05	Replace the idle control valve with a new one
S08	Replace spark plug no. 1 with a new one
S14	Replace ignition coil no. 1 with a new one
S20	Replace the fuel pump with a new one
S21	Replace the fuel hose with a new one
S22	Replace the throttle switch with a new one

The symptom data form the observable facts that the owner reports during a consultation. They were defined with the expert so that each one can be perceived with certainty by the owner without the use of a scanner. The symptoms fall into several groups: general indications of power loss such as a drop in engine RPM; air-conditioner-related behaviour such as an RPM drop of about 100 RPM when the air conditioner is switched on; acceleration and load behaviour such as the loss of power on an incline or black exhaust smoke; ignition-related checks such as the absence of any change in engine sound when a particular ignition coil cable is removed, and the change observed after swapping coils; and fuel- and throttle-related indications such as a clogged fuel filter, a leaking fuel hose, or a throttle valve that becomes clean after cleaning. Table 4 lists a representative subset of these symptoms.

Table 4. Representative symptom data

ID	Symptom
G01	Engine RPM drops
G02	RPM drops by about 100 RPM when the air conditioner is switched on
G05	RPM drops by 100 RPM or more
G06	Power is lost or absent on an incline
G08	Black exhaust smoke
G09	Air flow / airmass hose looks unfit (torn, cracked, and so on)
G11	Continuous engine misfire / popping at any RPM
G13	No change in engine sound when ignition coil cable no. 1 is removed
G28	Fuel filter clogged (no fuel exits the filter outlet when opened)
G29	Fuel hose leak (drips smelling of fuel)
G33	Throttle valve becomes clean after cleaning with carburetor cleaner

3.2. Rule Base and Inference Example

The relationships between symptoms and problems are encoded as a decision table and translated into 22 production rules, one per problem. Each rule connects a specific combination of symptoms to a single problem and its solution, following the general form of Equation (1). Table 5 presents a representative subset of the rule base; the symptom identifiers used in the rules correspond to the symptom data G01–G33 in the knowledge base.

Table 5. Representative production rules of "Si Pak-E"

Rule	IF (symptoms) THEN (problem)	Solution
R1	IF G01 ∧ G02 ∧ G03 ∧ G04 THEN P01 (ICV dirty)	S01
R2	IF G01 ∧ G02 ∧ G03 THEN P02 (ICV damaged)	S05
R3	IF G01 ∧ G05 ∧ G06 ∧ G07 ∧ G08 ∧ G10 THEN P03 (air flow hose dirty)	S02

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Rule	IF (symptoms) THEN (problem)	Solution
R4	IF G01 ∧ G05 ∧ G06 ∧ G07 ∧ G08 ∧ G09 THEN P04 (air flow hose damaged)	S06
R5	IF G01 ∧ G11 ∧ G12 ∧ G13 ∧ G19 THEN P12 (ignition coil no. 1 damaged)	S14
R6	IF G01 ∧ G11 ∧ G13 THEN P06 (spark plug no. 1 damaged)	S08
R7	IF G25 ∧ G26 ∧ G27 ∧ G28 THEN P19 (fuel filter dirty)	S03
R8	IF G29 THEN P20 (fuel hose leaking)	S21
R9	IF G30 ∧ G31 ∧ G32 ∧ G33 THEN P21 (throttle valve dirty)	S04

To illustrate how the inference engine operates, consider an owner who observes that the engine RPM drops (G01), that the RPM falls by about 100 RPM when the air conditioner is switched on (G02), that a deceleration occurs the moment the air conditioner is turned on (G03), and that, after cleaning the idle control valve with carburetor cleaner, the valve functions again and is clean (G04). The forward chaining engine places these four facts in working memory and matches them against the rule base. Rule R1, whose premise is exactly G01, G02, G03, and G04, is satisfied and therefore fires, asserting the conclusion P01, namely that the idle control valve is dirty. Because a goal problem has been reached, the consultation stops and the system displays the problem, its explanation, and the recommended solution S01, which is to clean the idle control valve using carburetor cleaner. Figure 3 shows the decision tree.

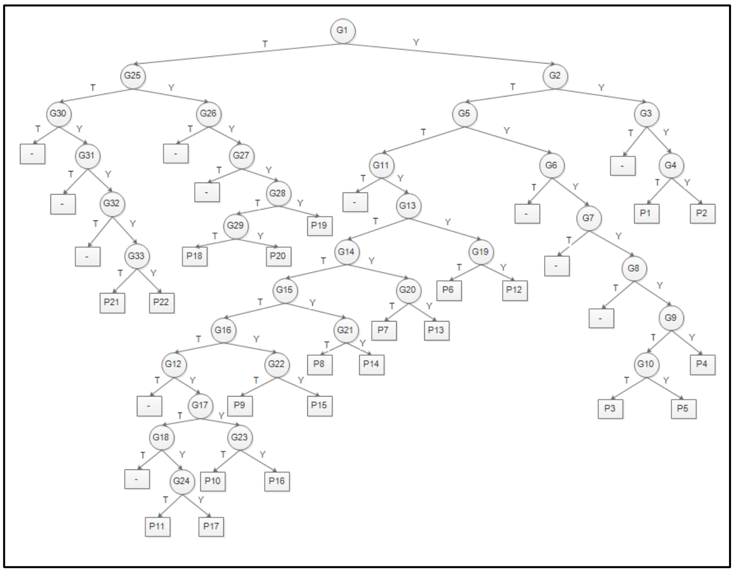

Figure 3. Decision Tree

3.3. System Design

The system design was expressed through data flow diagrams, an entity relationship diagram, the database design, and the user-interface mockups. At the highest level, the context diagram in Figure 4 shows that “Si Pak-E” interacts with three external entities. The administrator manages the user accounts and reviews the suggestions submitted for the system. The expert supplies and maintains the domain knowledge, namely the problem data, symptom data, solution data, and rule data, and may review the consultation history. The registered BMW E36 owner submits the observed symptoms during a consultation and receives the diagnosis result, the explanation, and the solution, and may print the consultation history.

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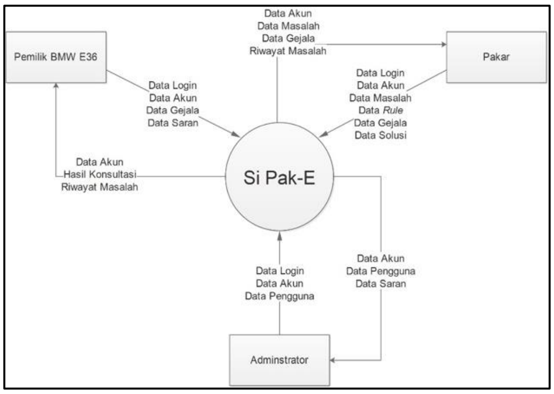

Figure 4. Context diagram of “Si Pak-E”

The context diagram was decomposed into the level-1 data flow diagram shown in Figure 5, which contains twelve processes covering registration, login and authentication, account recovery and verification, account management, the management of the four knowledge components, the consultation process, the consultation history, the suggestion facility, and the role-specific dashboard, together with five data stores. The processes composed of more than one elementary operation, in particular the management of the problem, symptom, solution, and rule data and the consultation process, were further decomposed into nine level-2 diagrams.

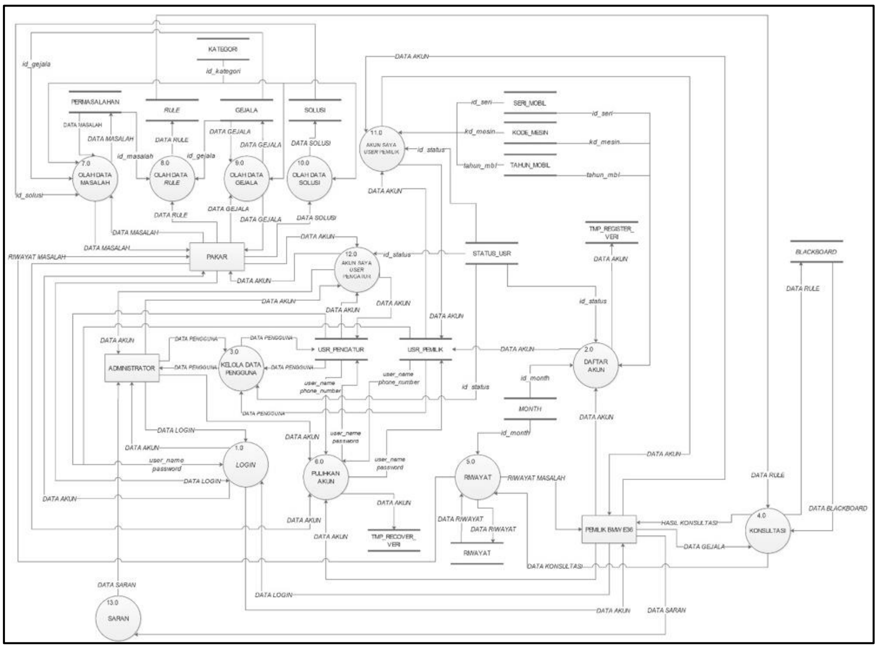
Figure 5. Level-1 Data Flow Diagram of “Si Pak-E”

The data requirements of these processes were modelled in the entity relationship diagram of Figure 6, which relates the knowledge entities, namely symptom, rule, problem, solution, and category, to the user entities, namely the owner account and the manager account, and to the consultation-history, suggestion, and blackboard entities. The rule entity is the associative entity between symptom and problem, so that a rule records which symptoms lead to which problem, while every problem is linked to exactly one solution.

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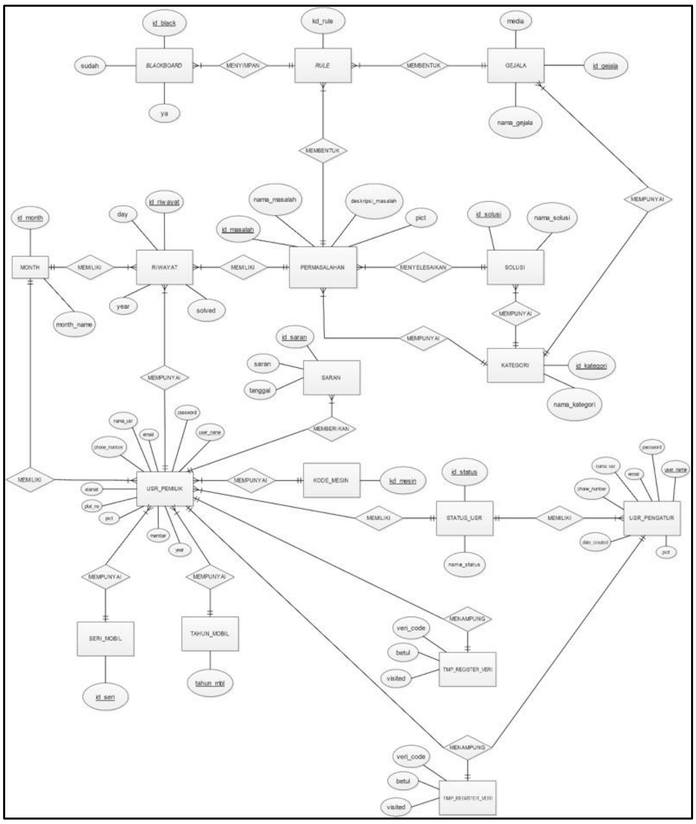

Figure 6. Entiry Relationship Diagram of “Si Pak-E”

The entity relationship diagram was translated into a physical design of sixteen MySQL tables. Among them, the blackboard table plays the role of the working memory of the inference engine: at the start of a consultation the applicable rules are copied into it, and the engine marks the rules that have already been evaluated together with the answers given by the owner, so that the state of the reasoning process is persisted while the consultation is in progress and is truncated once a conclusion is reached. The remaining tables store the knowledge components, the account and verification data, the consultation history, and the suggestions. User-interface mockups were produced for every page of the three roles before implementation, and the two pages that carry the diagnostic function of the system are presented in Sub-section 3.4.

3.4. Implementation

The design was implemented as a web application using PHP as the server-side language, HTML, CSS, JavaScript, JSON, and the Bootstrap framework for the responsive interface, with MySQL through phpMyAdmin as the database. The application provides authentication and account management, create-read-update-delete facilities for the knowledge components used by the expert, dashboards tailored to each user role, a consultation module for owners, and a consultation-history feature whose records can be printed as a report. During a consultation, the system retrieves the rules from the knowledge base, presents the relevant symptom questions in the order dictated by the rules, records the user’s answers in a temporary working area, and applies the forward chaining inference to determine the resulting problem and solution. Access to the consultation module is restricted to registered owners, ensuring that the diagnostic knowledge is provided only to authenticated members.

The three user roles are clearly separated by their access rights. The administrator can view and remove the accounts of expert users and view the registered owner accounts, but does not modify the knowledge base. The expert is responsible for the knowledge itself and can add, update, and delete the

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problem data, symptom data, solution data, and rule data, thereby keeping the system current as new cases are encountered; the expert can also review the consultation history. The registered owner uses the system to perform a consultation, viewing the resulting problem, its explanation, and its solution, and can manage their own account and inspect their personal consultation history. A dashboard tailored to each role presents the most relevant information immediately after login, while a suggestions feature lets owners send feedback that the administrator can review. This separation of duties mirrors the structure of an expert system, in which the development environment used by the expert to maintain the knowledge base is distinct from the consultation environment used by the owner to obtain a diagnosis.

3.5. Functional Testing Result

Following the design in Sub-section 2.5, the system was tested using the black-box method. The test suite comprises 36 test cases covering every process reachable by the three roles, and these test cases were executed as 95 individual scenarios of valid, invalid, and empty input. The distribution of the scenarios over the three roles is summarized in Table 6.

Table 6. Distribution of the black-box test scenarios

User role	Test cases	Scenarios executed	Accepted	Pass rate
Administrator	10	28	28	100%
Expert	17	42	42	100%
Registered owner	9	25	25	100%
Total	**36**	**95**	**95**	**100%**

For all 95 scenarios the observed output was identical to the expected output, so every scenario satisfied the acceptance criterion and no defect was recorded. Table 7 summarizes representative results of the black-box testing.

Table 7. Representative black-box testing results

Process	Test scenario	Expected	Result
Login	Submit empty username/password	Yes	Accepted
Login	Submit wrong credential combination	Yes	Accepted
Login	Submit valid credentials	Yes	Accepted
Add rule	Submit a rule code that already exists	Yes	Accepted
Add rule	Submit a valid, complete rule	Yes	Accepted
Consultation	Select symptom options until result	Yes	Accepted
Consultation	Leave symptom option empty	Yes	Accepted

3.6. Knowledge-Base Verification Against the Expert

The functional testing confirms that the software behaves as specified, but not that the knowledge it encodes is correct. The rule-coverage verification described in Sub-section 2.5 was therefore carried out. All 22 production rules were traced as consultation cases: for each rule, the symptom set forming its premise was entered through the consultation module, and the resulting problem and solution were compared with the entry of the expert's decision table. The outcome is summarized in Table 8.

Table 8. Result of the knowledge-base verification against the expert's decision table

Problem group	Rules traced	Cases in agreement	Agreement
Idle control valve (P01–P02)	2	2	100%
Air flow / airmass (P03–P05)	3	3	100%
Spark plugs (P06–P11)	6	6	100%
Ignition coils (P12–P17)	6	6	100%

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Problem group	Rules traced	Cases in agreement	Agreement
Fuel system (P18–P20)	3	3	100%
Throttle (P21–P22)	2	2	100%
Total	**22**	**22**	**100%**

In all 22 cases the system identified the same problem and recommended the same solution as the expert's decision table, giving an agreement rate of 22 of 22, or 100%. The verification also confirmed that no rule was unreachable and that no symptom combination fired more than one rule, so the rule base is both complete with respect to the decision table and free of conflicts. Taken together with the functional results, this indicates that the encoded rule base faithfully represents the expert's knowledge of power loss problems on the BMW 3 Series E36, and that the inference engine applies that knowledge without distortion.

4. DISCUSSION

The results demonstrate that forward chaining is an appropriate inference strategy for the symptom-driven diagnosis of automotive power loss. Because the owner begins from a set of observable symptoms and the system reasons toward the underlying problem, the data-driven nature of forward chaining maps directly onto the diagnostic task, allowing the most probable problem and its solution to be reached through a transparent sequence of rule firings. The 100% agreement obtained over the 22 traced rules shows that this transparency does not come at the cost of fidelity: the reasoning of the expert is reproduced exactly, and it can at the same time be explained to the owner step by step and inspected or updated by the expert without retraining.

The findings are consistent with prior research that applied rule-based reasoning to vehicle diagnosis. The mobile motorcycle-damage diagnosis system of Fitri Naryanto et al. [14], the knowledge-based system for three-wheeled motorcycle engine faults of Ary Setyadi et al. [15], and the web-based diagnosis of electric-vehicle damage of Kurniawan and Christanto [16] all reported that rule-based reasoning could reliably identify vehicle faults from user-supplied symptoms, and the agent-based car failure diagnosis system of Mostafa et al. [11] reached a similar conclusion for general car failures. The present work aligns with these results while extending the application to a specific and previously unaddressed target, namely the power loss problems of the BMW 3 Series E36, whose 22 problems, 33 symptoms, and 22 solutions were elicited directly from a specialist mechanic. Compared with diagnosis systems in the medical and agricultural domains that combine forward chaining with uncertainty handling such as the certainty factor, the Dempster-Shafer theory, or Bayesian probability [4], [23], [29], the proposed system relies on deterministic rules because the symptoms of E36 power loss, as defined with the expert, are observable with certainty and do not require probabilistic weighting; this keeps the inference simple and the explanations clear.

The contribution of this work to the discipline of informatics and computer science is threefold. First, it demonstrates knowledge preservation as an engineering outcome: tacit diagnostic expertise that existed only in the practice of a small number of specialist mechanics has been elicited, formalized as a 33 × 22 decision table, and made explicit as a machine-executable rule base that can be inspected, versioned, and maintained by the expert through the system itself. Second, it contributes an argument for the continued relevance of transparent, rule-based reasoning in a field increasingly dominated by data-driven models. Data-driven fault diagnosis requires large labelled fault datasets that do not exist for a discontinued, low-volume vehicle such as the E36, and its conclusions are difficult to explain to a non-expert user who must act on them physically. A rule base built from expert elicitation needs no training data, produces an auditable inference trace, and can be corrected by editing a single rule; the verification reported in Sub-section 3.6 is possible precisely because every conclusion can be traced to an explicit premise. Third, it provides a reusable methodological template, namely the pairing of functional black-box testing with rule-

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coverage verification against the expert's decision table, which other knowledge-based diagnostic systems in narrow domains can adopt to report evidence that is quantitative without requiring a large field trial.

From a practical standpoint, the main contribution of "Si Pak-E" is accessibility. By encoding scarce specialist knowledge into a web application and restricting consultation to registered owners, the system makes expert-level guidance available to E36 owners who are far from any authorized or specialist workshop, addressing precisely the gap identified at the outset of this study. The study nevertheless has limitations. The knowledge base is confined to power loss problems of moderate-to-low difficulty on a standard, unmodified E36 engine and excludes faults that require a scanner or that involve compression and pistons. The rule base is deterministic, so an owner who observes only part of a symptom set receives no conclusion rather than a ranked list of candidates. Furthermore, the evaluation reported here establishes functional correctness and fidelity to the expert's decision table, but it is not a field trial: the agreement rate is measured against the expert's codified reasoning rather than against confirmed physical repairs on a large sample of cars. A prospective field study, in which the diagnoses produced by the system are compared with the fault actually found and fixed at a workshop, would provide external validity and is left for future work.

5. CONCLUSION

This research designed and built "Si Pak-E", a web-based expert system that identifies power loss problems on the BMW 3 Series E36 engine using forward chaining and recommends the corresponding solution. The knowledge of a BMW specialist mechanic was formalized into a knowledge base of 22 problems, 33 symptoms, 22 solutions, and 22 production rules derived from a 33 × 22 decision table, and implemented in PHP, MySQL, and Bootstrap with three separated user roles. The evaluation produced two quantitative results: black-box testing accepted 95 of 95 scenarios across 36 test cases and three roles, and rule-coverage verification reproduced the expert's conclusion, both the problem and the solution, in 22 of 22 traced cases. The system therefore reasons as the expert does, and it does so through an inference trace that the owner can follow and the expert can audit.

For informatics and computer science, the significance of this result lies less in the application than in what it shows about knowledge-based methods. It establishes that, in a narrow domain where labelled fault data cannot exist because the vehicle is discontinued and the population is small, expert elicitation combined with deterministic rule-based inference remains not merely usable but preferable: it needs no training corpus, yields explanations that a non-expert can act on physically, and converts perishable tacit expertise into an explicit, maintainable, and transferable knowledge artifact. The pairing of functional black-box testing with rule-coverage verification against the expert's decision table is offered as a reusable evaluation template for knowledge-based diagnostic systems that face the same data scarcity.

Future research should proceed along three measurable directions. First, a prospective field trial with registered owners, in which each system diagnosis is compared with the fault subsequently confirmed at a workshop, would allow diagnostic accuracy, precision, and recall to be reported against physical ground truth rather than against the decision table. Second, the knowledge base should be extended to the remaining fault classes of the E36 and to other BMW 3 Series production codes, and the growth of the rule base should be evaluated in terms of the number of rules, the depth of the inference, and the response time of the consultation. Third, the deterministic rule base should be compared experimentally with a variant that incorporates certainty factors, so that the trade-off between the transparency of deterministic rules and the tolerance of incomplete symptom sets can be quantified rather than assumed.

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