Glucose and Lactate Biosensors

BGN: 2265V

March 28, 2025

3385 Words, 9 Figures and Tables

Contents

1 Part A: Evaluation of Commercial Glucose Biosensors

1985 Words, 8 Figures and Tables

Abstract

We evaluated the performance of three commercial glucose biosensors using simulated blood samples. Handheld meters were used to analyse test solutions of known glucose concentration. Class data were pooled and analysed for accuracy and precision. We also qualitatively assessed design and usability using a group-defined rubric. Results show that while sensors perform reliably within physiological ranges, accuracy declines at extreme concentrations or in the presence of interferents. These findings have implications for diabetic self-monitoring and highlight areas for improvement.

1.1 Introduction

Glucose biosensors are widely used for self-monitoring by diabetic individuals, typically in the form of disposable test strips [8]. These enable quick and accessible blood sugar testing without laboratory support. Most systems rely on enzymatic reactions, commonly involving glucose oxidase or glucose dehydrogenase, that generate an electrical signal proportional to glucose concentration via redox chemistry.

The first glucose biosensor was developed in the 1960s [2, 6], and devices have since improved in sensitivity, specificity, and resistance to interference. Beyond clinical care, glucose sensors are also used in food production and biotechnology. However, limitations remain: measurement accuracy can be compromised by sample handling, user error, or matrix effects. ISO 15197:2013 permits a ±15% error [4], which may still pose clinical risk. Continuous glucose monitors (CGMs) offer improved temporal resolution but require more complex infrastructure.

Glucose biosensors typically rely on enzymatic oxidation of glucose by glucose oxidase (GOx) or glucose dehydrogenase (GDH), producing electrons that generate a current proportional to glucose concentration. GOx produces hydrogen peroxide, which is electrochemically detected at the electrode surface [7]. In contrast, GDH systems use electron mediators (such as PQQ or FAD) to transfer electrons directly to the electrode, enabling oxygen-independent measurements [5]. These systems are integrated into test strips containing a capillary sample chamber, working and reference electrodes, and conductive pads, all connected to a meter that amplifies and processes the signal to display glucose concentration in mmol/L.

Frequent glucose monitoring, often exceeding 1,000 tests annually for insulin-treated diabetics, demands sensors that are not only accurate but also highly usable. Features such as strip orientation, screen readability, and minimal setup time directly affect compliance and safety in daily life, particularly for users with impaired vision or dexterity.

In this study, we investigated both the analytical performance and user-friendliness of three commercial glucose meters. We assessed their accuracy, susceptibility to interference, and suitability for self-monitoring, alongside a qualitative evaluation based on ease of use and clarity.

1.2 Materials and Methods

Three glucose meters were tested: Accu-Chek, True Metrix, and eBWell, each with their respective test strips containing immobilised enzymes and redox mediators for amperometric glucose detection.

Groups used prepared solutions mimicking blood plasma. Samples A*–D* (3.9–7.2 mM) had low haematocrit to assess matrix effects. Interference was evaluated using sample G* (glucose + lemon juice) and F* (sucrose only) [1].

Measurements followed manufacturers' instructions, applying 1–2 μL of sample per strip. Each group collected at least one replicate per sample. Accu-Chek used glucose oxidase (oxygen-dependent), while the others used oxygen-independent glucose dehydrogenase variants [3].

All class data (157 readings) were compiled. Accuracy, precision, and clinical reliability were assessed using MARD, CV, and Clarke Error Grids. A group-defined rubric was also used to evaluate usability, with weighted scores for clarity, feedback, and ease of operation.

1.3 Results and Discussion

1.3.1 Quantitative Evaluation of the Glucose Test-Strip

Figure 1 shows the raw measurement results across all three biosensor systems. To evaluate sensor performance, we proceed by quantifying *accuracy*, *precision*, and overall *clinical reliability*. These measures help us assess how reliable each device would be for a diabetic patient monitoring their glucose. Additionally, we seek to evaluate how each sensor responds to known sources of electrochemical interference and whether observed variation has meaningful clinical consequences.

We begin with Figure 2, where we evaluate overall sensor accuracy and precision. Accuracy is quantified using the Mean Absolute Relative Difference (MARD), which gives the average percentage deviation of the measured glucose from the true reference value:

	12.03.25 Group B			13.03.25 Group A		13.03.25 Group B		14.03.25 Group A			12.03.25 Group A		10.03.25 Group A	
Glucose Sensor						*eBwell*								
Strip Expiry Date						Jan-25								
Sample glucose(mg/dL)	**A**			**B**		**C**		**D**			**E**		**F**	
A* - 70		5.3	6.3	6.2		6	8.6	6.4	6.7	6.9	5.8		4.6	
B* - 90		6.6		7.5		5.9	9.2	7.7	7.5	7.3	6.7		5.8	
C* - 110		9.4	10.9	9.4	9.1	13.9	14.6	10.2	10.1	9.6	9.4	10.3	8.6	
D* - 130		10.8		11.1		16.7	18.1	11.3	11.3	11.9	10.6		8.9	
F* - 1000	1.4	2.1	low	2.2	2.3	2.6	2.8	5.3	4.8	4.9	1.9	1.9	11	
G* - 90 + Lemon		8.3		8.3	8.1	10.3	10.8	9	8.3	8.5	8.3	8.3	8.7	
H* - 100		7.9									8.8		7.4	

Glucose Sensor						*TrueMetrix*								
Strip Expiry Date														
Sample glucose(mg/dL)	**A**			**B**		**C**		**D**			**E**		**F**	
A* - 70		2.6		3.8				E-2 error for both machines			2.6	2.8	2.6	
B* - 90		3.2		3.9	3.8			3.8	3.3	3.7	3.2		3.2	
C* - 110		5.1		4.9				4.7	E-2	4.7	4.6	5.1	4.7	
D* - 130		6		5.4	5.8			5.9	8.1	5.3	6		6.1	
F* - 1000		low	4.1	error!				E-2	E-0	E-2	N/A		error - E2	
G* - 90 + Lemon		3.8		3.6	3.9			E-2			E-02	3.8	3.9	
H* - 100		4.5	4.1								E-02	4.3		

Glucose Sensor						*Accu-check Aviva*								
Strip Expiry Date						1/31/202	CODE: 690731							
Sample glucose(mg/dL)	**A**			**B**		**C**		**D**			**E**		**F**	
A* - 70	3.2	3.1	3.1	3.1		3.6		3.1	3	3.2	3		3.1	
B* - 90		3.3		4.1		4.2		4.1	4.1	4	3.4		3.4	
C* - 110	4.9	5		4.9		5.7		5	5.2	5.1	5.1	5	4.6	5.2
D* - 130	6	error	6	6.1		6.1		E-7 error	6.1	5.9	5.9		6.2	
F* - 1000	Low	1.1		0.9	1.1	1.1	1.1	2.7	2.7	2.8	1.2		0.8	
G* - 90 + Lemon	3	4.2		4		4.2		4.6	4.1	4.2	4.2		4	4.1
H* - 100		4.5									4.4			

Figure 1: Measured glucose concentrations across three biosensor systems: (top) eBwell, (middle) True Metrix, and (bottom) Accu-Chek. Each panel displays readings for a range of test solutions with known glucose concentrations.

$$\text{MARD} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{G_i^{\text{measured}} - G_i^{\text{reference}}}{G_i^{\text{reference}}}\right| \times 100$$

Precision is assessed using the coefficient of variation (CV), which reflects the consistency of repeated measurements for the same concentration:

$$\text{CV} = \frac{\sigma}{\mu} \times 100$$

Here, σ is the standard deviation and μ is the mean. Low MARD and CV indicate better sensor performance.

From Figure 2, we see that Accu-Chek outperforms the other sensors in both accuracy and precision. True Metrix performs moderately well, while eBwell performs the worst on both metrics. These observations are further supported by the sensor-specific standard deviations across solutions, summarised in Table 1. eBwell consistently shows greater variability, with some SD values over $3\,\text{mmol}\,\text{L}^{-1}$, while Accu-Chek remains stable throughout.

The error rate (i.e. non-numeric or failed readings) provides further information

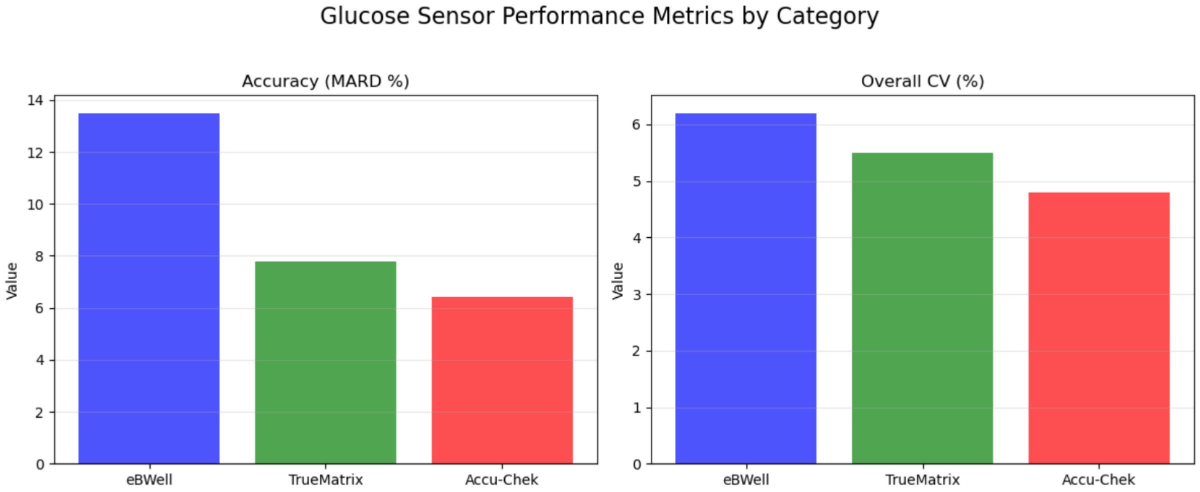

Figure 2: Overall Performance Metrics for the 3 Different Sensors

Table 1: Standard Deviation of Glucose Readings by Sensor for Each Solution (A*–F*)

Solution	eBwell (mmol/L)	True Metrix (mmol/L)	Accu-Chek (mmol/L)
A* – 70	1.057	0.522	0.172
B* – 90	1.040	0.314	0.385
C* – 110	1.878	0.206	0.269
D* – 130	3.027	0.868	0.106
F* – 1000	2.679	—	0.825

regarding the suitability of these sensors. As shown in Table 2, eBwell had the lowest error rate overall (1.49%), while True Metrix had a much higher failure rate of 22.92%. Accu-Chek had an acceptable error rate of 4.84%.

Table 2: Summary Statistics of Glucose Readings per Sensor

Sensor	Valid Readings	Error Readings	Total	Error Rate (%)
eBwell	66	1	67	1.49
True Metrix	37	11	48	22.92
Accu-Chek	59	3	62	4.84

To statistically confirm sensor differences, we performed ANOVA testing (Table 3). A one-way ANOVA shows highly significant differences between the groups ($p < 10^{-17}$), indicating that at least one sensor differs from the others. Pairwise ANOVA confirms that eBwell differs significantly from both True Metrix and Accu-Chek, while the latter two are statistically similar. That is, given the measurements we have observed, there is not sufficient statistical evidence at the 5% confidence level that True Metrix and Accu-Chek produce different results.

To assess clinical relevance, we used the Clarke Error Grid (Figure 3), which classifies

Table 3: ANOVA Results Comparing Glucose Sensors

Comparison	F-statistic	p-value	Significant?
One-Way ANOVA (all sensors)	52.69	2.78×10^{-18}	Yes
eBwell vs True Metrix	40.49	5.85×10^{-9}	Yes
eBwell vs Accu-Chek	74.24	2.82×10^{-14}	Yes
True Metrix vs Accu-Chek	2.29	0.133	No

each reading based on its potential to lead to harmful clinical decisions. This analysis provides insight not only into analytical performance but into how any inaccuracies might affect patient safety.

The Clarke Error Grid divides glucose measurements into five zones (A to E). Zone A represents values that are clinically accurate and would result in correct treatment decisions. Zone B includes values that deviate from the reference but would not lead to inappropriate clinical action. Zone C involves unnecessary correction. Zone D reflects a failure to detect and treat abnormal glucose. Zone E represents dangerously incorrect treatment. These classifications allow us to assess whether a given measurement might have real-world consequences.

Accu-Chek and True Metrix have most of their readings within Zones A and B, which represent no clinical risk. eBwell, however, shows a number of readings falling in Zones C and E, categories associated with dangerous or incorrect treatment decisions. This confirms that the inaccuracies seen in Figure 2 and the variability in Table 1 translate into real clinical concerns.

We then evaluated each sensor's susceptibility to interfering substances by comparing its response to C* (pure glucose) with that of F* (sucrose only) and G* (glucose with lemon juice/ascorbic acid).

In theory, sucrose (F*) should yield negligible glucose readings, as it is not directly acted upon by glucose oxidase. While Accu-Chek behaved accordingly, True Metrix and eBwell still reported readings of approximately $4.1\,\mathrm{mmol\,L^{-1}}$ and $3.6\,\mathrm{mmol\,L^{-1}}$, suggesting poor selectivity or cross-reactivity.

The G* solution tested the impact of ascorbic acid (vitamin C), a known electrochemical interferent. Accu-Chek and True Metrix's measurements both slightly decreased, but remained within an acceptable range. eBwell produced an inflated reading of $8.8\,\mathrm{mmol\,L^{-1}}$, significantly above the expected $5.0\,\mathrm{mmol\,L^{-1}}$. This suggests a failure of interference compensation in the eBwell sensor.

Taken together, these comparisons reinforce the conclusion that eBwell exhibits significantly poorer specificity and may be more vulnerable to non-glucose reducing agents in complex samples. This is particularly concerning in real-world settings where dietary substances or medications could alter results.

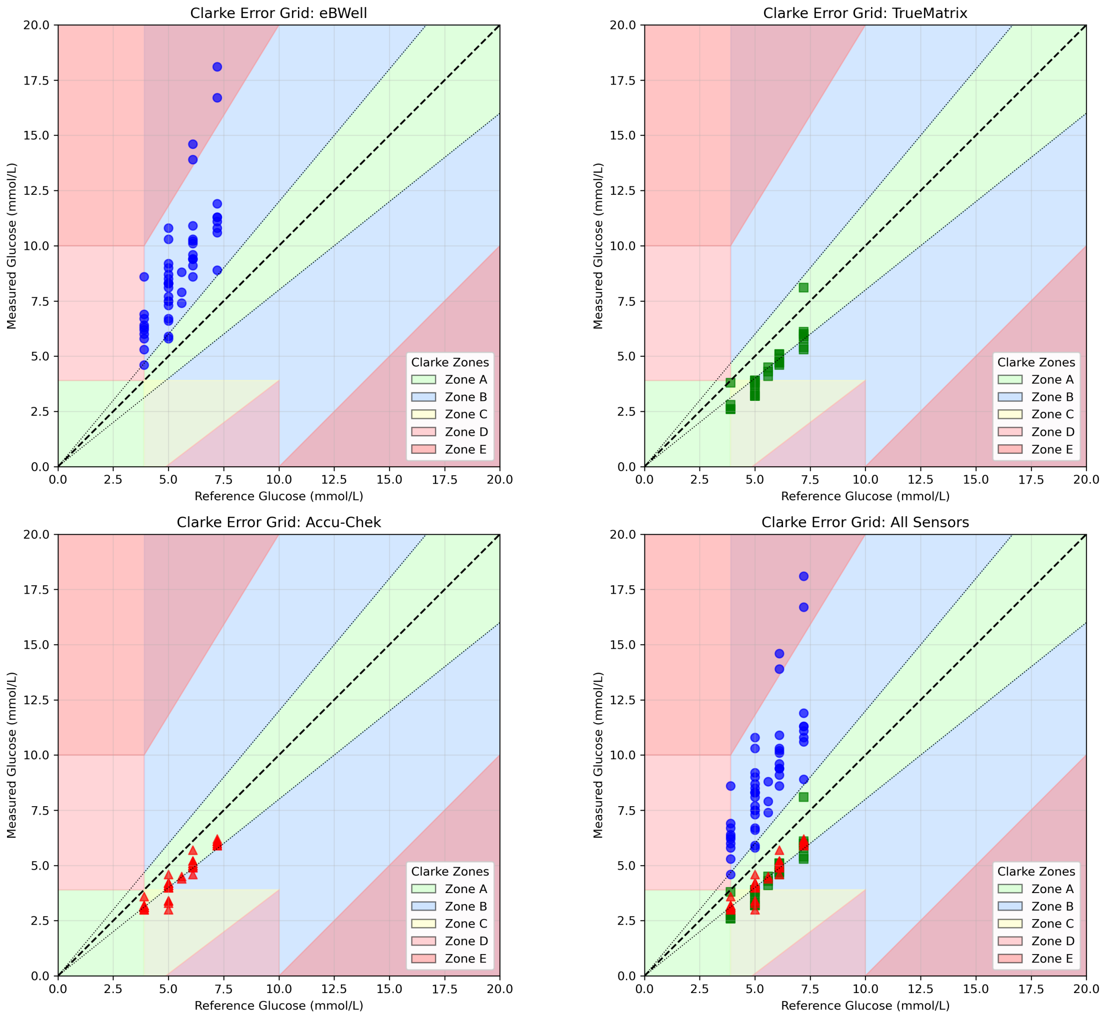

Figure 3: Clarke Error Grid Plots for all 3 Different Glucose Sensors

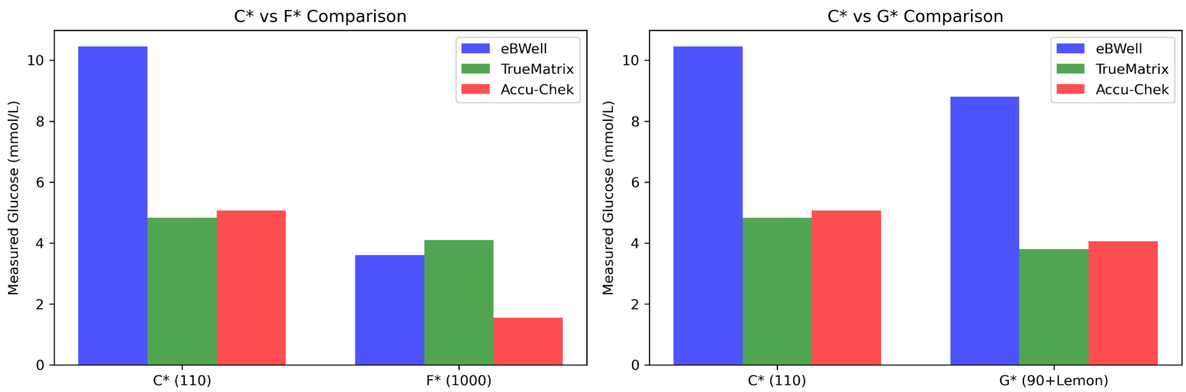

Figure 4: Comparison of C* Concentration Levels with F* and G*

Clinical Implications. Our study focused on low haematocrit samples, which typically result in slightly elevated glucose readings due to a higher plasma-to-cell ratio, the eBwell device still reported disproportionately high glucose concentrations compared to both True Metrix and Accu-Chek. This suggests a failure in calibration or interference compensation, rather than a haematocrit-related issue. Contributing factors may include sensor overactivity, poor filtering of interfering substances, or an inadequately generalised reference curve. These inaccuracies raise concerns about clinical reliability, especially in patients with variable sample conditions.

For diabetic users relying on accurate readings for insulin dosing, such overestimation could lead to overtreatment and a heightened risk of hypoglycaemia. Inconsistent precision further erodes user confidence. Based on our findings, we would not recommend the eBwell sensor for clinical use without improved compensation mechanisms. Among the tested devices, Accu-Chek remains the most robust and reliable.

1.3.2 Qualitative Evaluation of Biosensor Design

In addition to evaluating performance from a technical perspective, we conducted a qualitative assessment of each biosensor's design and usability. This is important, as diabetic users rely on these systems in real-world settings, often multiple times per day, where factors such as readability, ease of use, and reliability play a key role.

As a group, we agreed on six core categories for assessment:

- Accuracy
- Precision
- Clarity of instructions
- Ease of use
- Display and readability
- Extent of Design
- User acceptance

We chose to score each category out of 5 and applied a weighting system that reflected the perceived clinical and user importance of each category. The final weightings were as follows:

True Metrix scored the highest overall (158/200), with strong marks for precision, instruction clarity, and user-friendliness, despite its physical shortcomings. The device's colour-coded instruction manual was particularly effective, and although the device was small and somewhat difficult to handle, its simple strip insertion and clear visual feedback

Table 4: Group-defined rubric for qualitative biosensor evaluation. Total scores are weighted out of 200.

Metric	**Weighting**	**Accu-Chek**	**eBWell**	**True Metrix**
Accuracy	9	3	1	4
Precision	8	2	1	4
Clarity of Instructions	4	2	3	5
Ease of Use	5	5	3	4
Display of Result	4	5	4	3
Extent of Design	2	5	1	3
User Acceptance	8	4	2	4
Total (/200)		138	78	158

made it intuitive once operational. However, one key issue was its initial failure to function, which may have affected real-world user confidence.

Accu-Chek (138/200) ranked closely behind. It had ergonomic design, fast response time, and intuitive interface. The ability to scroll through history and its clear result display contributed to positive user impressions. However, slightly lower scores for accuracy and precision affected its overall mark. That being said, these initial analyses were performed without full access to other groups data, and hence these initial assessments should be updated: we clearly ascertained Accu-Chek's superior precision and accuracy in the previous section. Its manual was clear but limited by tiny text and lack of diagrams.

eBWell scored significantly lower (78/200), largely due to usability challenges. The requirement to reset the device using a separate chip, unclear strip orientation, and minimalistic instructions made operation less intuitive. Although it included a history function, navigation was awkward due to the single-button interface. Additionally, it had the slowest response time and no graphical prompts. While it delivered consistent readings, concerns about overestimation and interference susceptibility further impacted confidence in its use.

In terms of our chosen weightings, we considered accuracy, precision, and user acceptance to be the most important for diabetic users. We therefore assigned weights of 9, 8, and 8 respectively. On reflection, this weighting still feels appropriate, as these three criteria directly influence treatment decisions and user safety. Clarity, usability, and display were deemed important but slightly secondary, while the design category served to capture less tangible aspects of the device experience.

Overall, despite True Metrix initially failing to operate, its usability and clarity of design allowed it to top our qualitative scoring. Accu-Chek followed closely, with consistent performance and intuitive feedback. eBWell, while functional, struggled across most categories and would benefit from a design overhaul to improve both usability and trust.

1.4 Conclusion

This investigation highlights both the strengths and limitations of current glucose test-strip technology for diabetic self-monitoring. While modern glucose meters perform reliably within the physiological range, notable gaps appear at extreme concentrations and in the presence of common interferents.

Accu-Chek showed the most consistent performance, combining good accuracy and precision with resistance to interference. It also scored well on usability. True Metrix performed well analytically, but its initial failure undermines confidence in real-world use. All test samples had low haematocrit levels. eBWell consistently overestimated glucose concentrations, likely due to an inadequate correction mechanism for haematocrit, resulting in systematically inflated readings. Its susceptibility to ascorbic acid and limited design further reduced its clinical suitability.

Usability-wise, Accu-Chek and True Metrix were intuitive, though both would benefit from clearer instructions and improved visual guides. eBWell's single-button interface, unclear strip orientation, and lack of feedback were persistent issues.

To be fit for purpose, a glucose test-strip system must combine analytical reliability with usability and robustness to interference. Improved haematocrit correction, interference filtering, and ergonomic features are needed to enhance safety and user confidence.

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2 Part B: Adapting Glucose Test Strips for Lactate Monitoring

1495 Words and 1 Figure and Table

2.1 Introduction

Lactate is a key indicator of tissue metabolism and is often used to assess oxygenation and metabolic stress. It is clinically relevant for conditions like septic shock, trauma, acute organ failure, and in evaluating athletic performance. Our company, which has had success with glucose test strips, is exploring the feasibility of adapting that technology for lactate measurement.

Lactate measurement is increasingly valued in critical care, largely due to new sepsis definitions that set a threshold of 2 mmol/L for potential septic shock, along with persistent hypotension [9]. (Older guidelines used a 4 mmol/L cutoff [9]) This shift highlights the need for accurate measurement of mild to moderate lactate elevations.

2.2 Clinical Relevance: Athletic and Medical Contexts

Athletic Performance Monitoring

During intense exercise, muscle metabolism may shift partially to anaerobic pathways, increasing lactate production. Monitoring lactate helps determine when the "lactate threshold" is reached, after which fatigue rises quickly [2]. Traditional lactate testing involves portable analysers or lab-based methods, but a strip-based approach could offer a quick, convenient alternative. Non-invasive or minimally invasive sports analytics are growing in popularity, and lactate levels are a recognised metric for understanding metabolic workload, recovery, and training gains.

Sepsis and Shock Management

In acute care settings, lactate is a recognised marker of tissue hypoperfusion and cellular stress [12]. Elevated lactate is frequently linked to shock states and is now considered an integral part of septic shock definitions, with 2 mmol/L as a key threshold [9]. Persistently high levels or poor lactate clearance over time often indicate poor outcomes [5]. A rapid test could guide decisions on fluid resuscitation, vasopressor therapy, and other interventions in the emergency department or ICU [5].

2.3 Mechanism of Lactate Biosensing

Electrochemical lactate biosensors are often adapted from glucose test strip designs, substituting the enzyme glucose oxidase with lactate oxidase (LOx). LOx catalyses the oxidation of lactate to pyruvate, generating hydrogen peroxide as a byproduct:

$$\text{Lactate} + O_2 \rightarrow \text{Pyruvate} + H_2O_2.$$

The hydrogen peroxide is subsequently oxidised at the electrode surface, producing an electrical current proportional to lactate concentration. Many strips include a redox mediator such as ferricyanide, which facilitates electron transfer between the enzyme and the electrode, enhancing signal stability and lowering the required operating potential [8].

From a manufacturing standpoint, this adaptation is straightforward: the underlying electrode design, mediator system, and strip architecture used in glucose sensors can remain largely unchanged. The primary modifications involve replacing the enzyme layer and updating calibration parameters to reflect lactate-specific kinetics. Notably, the Michaelis-Menten constant (K_m) of lactate oxidase typically lies in the millimolar range, which aligns well with physiological and pathological concentrations of lactate observed in blood and sweat [8]. This makes LOx-based biosensors especially suitable for real-time, point-of-care monitoring applications.

Sensor Output and Analytical Range

The current generated at the electrode surface is governed by Michaelis-Menten kinetics:

$$I_{\text{enz}} = \frac{I_{\max}[S]}{K_M + [S]}$$

This implies a nonlinear relationship between lactate concentration and sensor output. As substrate concentration $[S]$ increases, the current I_{enz} rises rapidly at first but then plateaus as the enzyme becomes saturated.

A plot of this relationship (Figure 5) illustrates that the most analytically useful range lies near the enzyme's K_M. Below this value, the sensor is highly responsive but more prone to noise; above it, the current saturates, limiting resolution. Choosing a lactate oxidase with a K_M in the low millimolar range aligns well with the physiological window of interest (e.g., 0–10 mmol/L in blood), allowing for both sensitivity and coverage of clinically relevant concentrations.

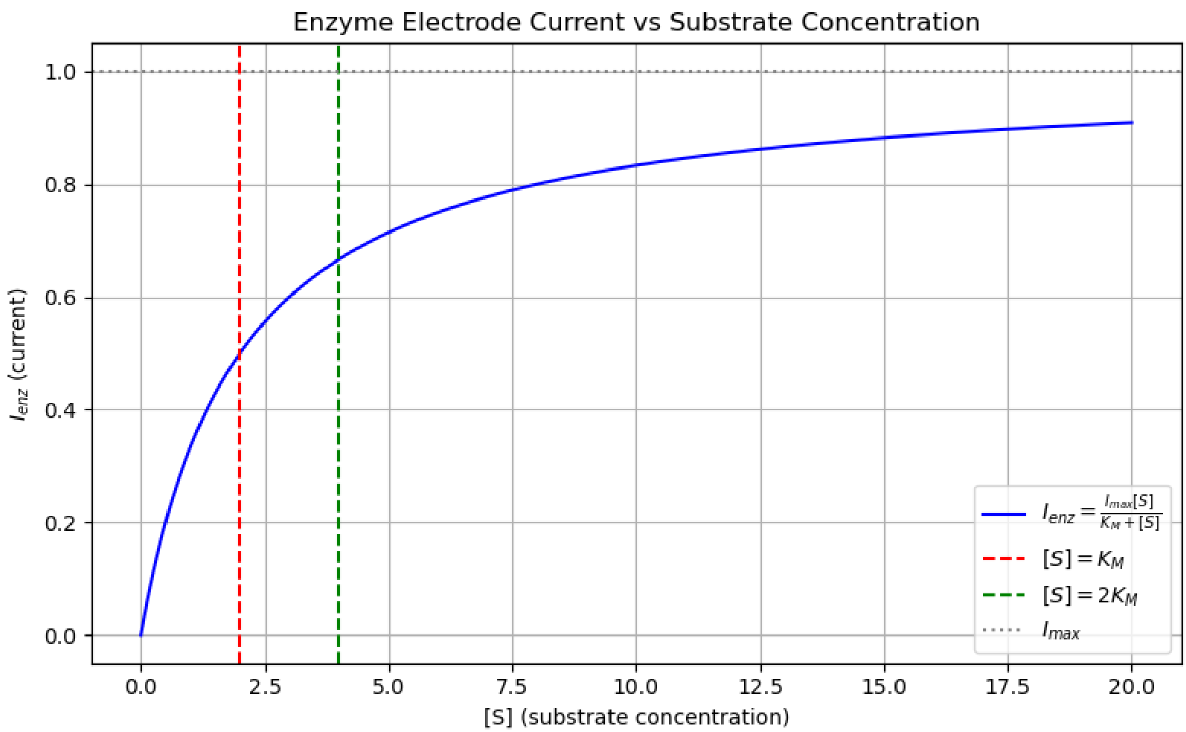

Figure 5: Simulated current response of a lactate biosensor governed by Michaelis-Menten kinetics. The current increases rapidly near the enzyme's K_M, here assumed to be 2 mmol/L, and saturates as substrate concentration increases. This defines the useful analytical range for quantification.

2.4 Key Measurement Ranges and Sample Types

Blood

In healthy individuals, blood lactate is usually below 2 mmol/L but can rise above 3–4 mmol/L during high-intensity exercise, where active recovery facilitates faster clearance in an intensity-dependent manner [10]. A clinical sensor should measure from near zero to at least 10 mmol/L. The needed blood volume (1–3 μL) is easily obtained from a finger-prick, mirroring glucose tests. Reusing existing capillary fill channels and strip sizes reduces manufacturing changes.

Sweat

Sweat lactate can be higher than blood lactate, often several millimolar during moderate activity and potentially tens of millimolar in extreme exertion [10]. Although there is substantial interest in sweat-based sensing, collecting enough sweat consistently is difficult. Potential contamination and evaporation are concerns. Adapting a strip format for sweat might be less straightforward than for blood, but the same enzyme chemistry could be used if a reliable collection method emerges.

Cerebrospinal Fluid (CSF)

CSF lactate is used to distinguish bacterial from viral (aseptic) meningitis, with elevated levels showing high diagnostic value for bacterial causes [4]. It can also increase significantly in certain neurological conditions, such as cerebral hypoxia or seizures. Normal values are generally under 2–3 mmol/L [4]. Although a strip-based method could, in theory, be used at the bedside to test CSF, the need for a lumbar puncture means the added convenience of a strip is likely less impactful compared to standard laboratory analysis.

2.5 Accuracy Considerations

Clinical Thresholds and Required Precision

Because some shock definitions hinge on a value of 2 mmol/L, sensors must be accurate in the 1–5 mmol/L range, ideally within 10–15% error [1]. In athletic uses, precision of relative changes may be more important than absolute values, but proper calibration is still necessary.

Sources of Interference

Blood contains substances like ascorbic acid and uric acid, which can interfere with electrochemical readings [13]. Protective layers and mediators, similar to those in glucose strips, help mitigate interference. Additional membranes may be required to minimise cross-reactivity and preserve accurate readings.

Oxygen Dependence

Some lactate oxidase sensors rely on oxygen as a co-substrate, making them sensitive to changes in oxygen levels [7]. Modern designs, however, often include mediators that lower oxygen dependence. This is advantageous in venous samples or in patients with poor perfusion.

2.6 Comparisons to Glucose Test Strip Technology

Many of the components used in glucose strip systems can be directly repurposed for lactate monitoring. The core meter hardware, including amperometric detection circuitry, display interface, and power supply, can remain unchanged. Only minor software updates would be needed to accommodate lactate-specific calibration. The strip layout, including carbon working and Ag/AgCl reference electrodes, remains suitable. Even the fluidic channel structures do not require significant alteration. In some cases, existing mediators such as ferricyanide may also be compatible with lactate oxidase, requiring only minor chemical adjustments.

However, some changes are essential. The enzyme layer must be reformulated to incorporate lactate oxidase instead of glucose-specific enzymes. Additional components, such as buffer systems, stabilisers, and surfactants, will need to be optimised to maintain enzyme activity and sensor response. Calibration algorithms must be updated to reflect lactate-specific ranges and thresholds, particularly around the clinically relevant 2 to 4 mmol/L region. Sensitivity may also need tuning to accommodate higher physiological concentrations of lactate, which can exceed 15 mmol/L in some settings.

There are clear advantages to adapting glucose strip infrastructure for lactate sensing. Most notably, the approach offers a low-cost route to development by leveraging existing production lines and materials. For users already familiar with glucose meters, the format remains intuitive and easy to use. Because the manufacturing process is already established, this could significantly reduce time to market and facilitate more rapid clinical deployment.

Nonetheless, key challenges remain. The demand for lactate monitoring is more niche and less frequent than glucose testing, which may limit commercial interest. High precision is required in the 2 to 4 mmol/L range, particularly in critical care applications such as shock or sepsis. Sweat-based collection poses additional challenges, as directing sweat onto strips reliably is not straightforward without sampling aids.

Glucose meters follow a well-established regulatory pathway in many regions [11]. Adapting these devices for lactate measurement typically requires updates to performance data and product labeling rather than a full de novo process. However, clinical validation is still essential to confirm safety and effectiveness under FDA or CE guidelines.

2.7 Lactate in Sepsis and Shock

Sepsis definitions increasingly highlight lactate above 2 mmol/L as a risk factor [6]. Previously, 4 mmol/L was a common threshold [6]. Persistent hyperlactatemia suggests poor perfusion or severe underlying disease [6]. Point-of-care lactate tests, particularly in emergency settings, can speed up decision-making for fluid management or vasopressor use. A rapid and reliable strip-based sensor could be valuable in such environments.

2.8 Potential Use in Additional Sample Types

Elevated CSF lactate (e.g., above 4 mmol/L) suggests bacterial rather than viral meningitis [3]. This makes lactate a useful biomarker in differential diagnosis, particularly when classical indicators are inconclusive or delayed. In remote clinics, rapid lactate measurement can also help identify critically ill patients early. Battery-powered meters and finger-prick sampling are especially valuable in settings where laboratory infrastructure is limited.

2.9 Advantages and Disadvantages of Biosensor-Based Lactate Analysis

Biosensor-based lactate tests offer several advantages. They provide rapid results, are portable, and require only a small blood droplet, making them ideal for urgent or point-of-care use. Manufacturing is also accessible, as glucose strip technology can be adapted with modest changes. With proper validation, these sensors could be used on blood, sweat, or cerebrospinal fluid. However, limitations include a smaller market than glucose monitoring, as lactate is not tested as frequently. Clinical thresholds around 2 mmol/L also require strict accuracy. Additionally, lactate elevation can result from various causes, which complicates interpretation and may limit standalone diagnostic use.

2.10 Conclusion

Lactate monitoring, whether in sports or in sepsis management, stands to gain from established glucose test strip technology. By exchanging glucose-specific enzymes for lactate oxidase, and adjusting calibration and protective layers to manage interferences, existing strip architecture can be repurposed cost-effectively. Potential applications range from pinpointing athletic lactate thresholds to rapidly identifying shock states. However, ensuring accuracy near clinically significant thresholds, such as 2 mmol/L for sepsis risk, requires careful engineering. Blood sampling remains straightforward, while sweat-based methods face technical hurdles. Nonetheless, this approach offers a promising route to broaden point-of-care lactate testing in diverse scenarios—sports, emergency, healthcare, and beyond.

References for Section B

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Appendix

Concentration of Glucose Across Measured Samples

Table 5: Concentration of glucose and hematocrit conditions

Concentration of glucose		**Low Hematocrit**
mg/dL	**mM**	
70	3.9	A*
90	5.0	B*
100	5.6	H*
110	6.1	C*
130	7.2	D*
1000 (sucrose)	29.2	F*
90 + ascorbic acid	5.0	G*

Valid and Error Readings per Sensor and Glucose Solution

Table 6: Valid and Error Readings per Sensor and Glucose Solution

Sensor	**Solution**	**Valid Readings**	**Error Readings**
eBWell	A* - 70	10	0
	B* - 90	9	0
	C* - 110	12	0
	D* - 130	9	0
	F* - 1000	12	1
	G* - 90 + Lemon	11	0
	H* - 100	3	0
True Metrix	A* - 70	5	1
	B* - 90	8	0
	C* - 110	7	1
	D* - 130	8	0
	F* - 1000	1	6
	G* - 90 + Lemon	5	2
	H* - 100	3	1
Accu-Chek	A* - 70	10	0
	B* - 90	8	0
	C* - 110	11	0
	D* - 130	8	2
	F* - 1000	10	1
	G* - 90 + Lemon	10	0
	H* - 100	2	0

Standard Deviation Across Different Sensors and Concentration Levels

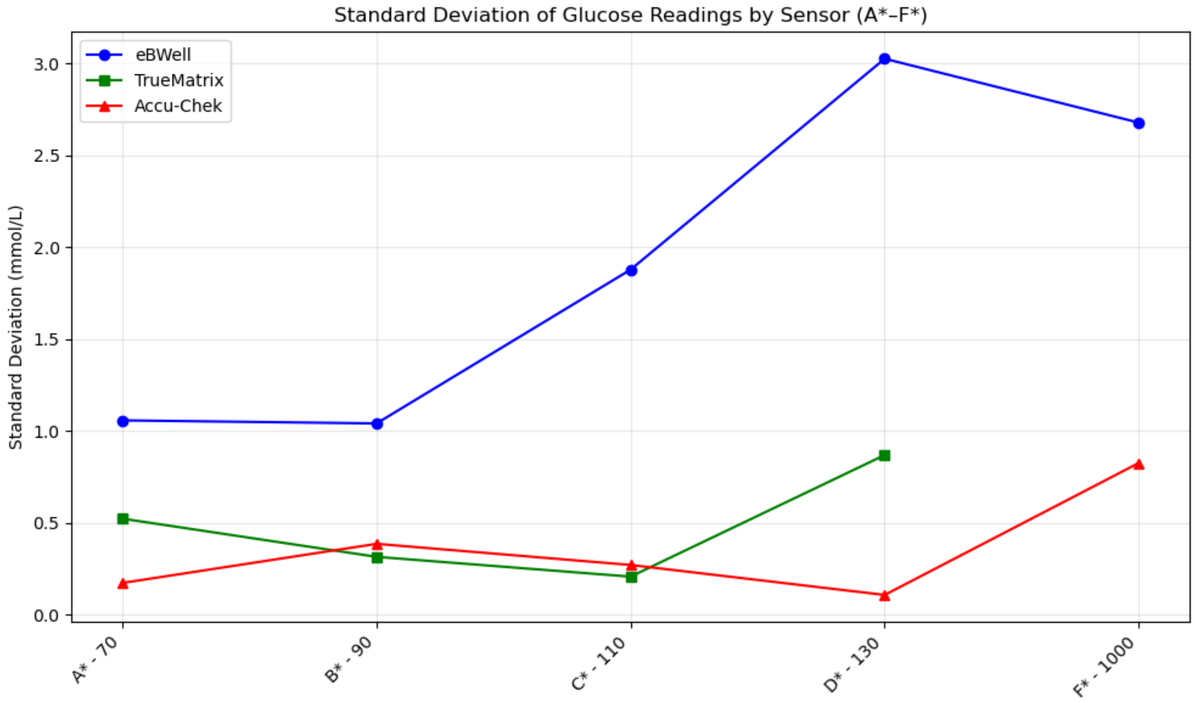

Figure 6: The measured standard deviation across the 3 different sensors across the 5 measured concentration values

Reproducibility and Scripts

The code and data that produced all of the plots in this report may be found on the author's GitHub, upon request.