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| 2026  CEO project PROPOSAL |  |

FlowGuardA person holding a phone

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# 01

## Executive summary

* The problem
* The solution at a high level (platform)
* Why this matters now
* Try tie down to the 6Cs
* Stakeholders

## MEET THE Dream team

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| ALKA  SEWRAJ | MORRIS  NKOMO | MULISA  MATODZI | NEIL  SMIT | TAAHIR  KOLIA |

## Hidden Failure in everyday banking

* 1. Customer Needs

The critical blind spot in how customers understand and experience debit order failures is that insufficient funds are rarely the sole culprit. While this remains the assumed cause, the reality is far more complex: a significant portion of failures stem from structural timing frictions embedded within the payment’s ecosystem itself. Settlement delays, cut-off times, the sequencing of multiple debits, and the persistent gap between ledger and available balances all create narrow windows in which a customer may appear financially liquid, yet still see a transaction fail.

This creates a significant visibility gap for customers, who are left with little clarity on why payments sometimes succeed and sometimes fail, often leaving them surprised by the outcomes. These failures carry real and uneven consequences, disproportionately affecting essential, high-value obligations like insurance premiums and loan repayments, categories where actual success rates fall materially below customer expectations. From the customer's perspective, the experience feels arbitrary and frustrating: funds may have been deposited, income scheduled to arrive the same day, and the intent to pay present, yet the payment still fails. The result is penalty fees, service interruptions, administrative friction, and a steady erosion of trust in their financial provider.

Within the FNB ecosystem, customers already have access to powerful but disconnected tools. Predictive balance modelling and real-time transaction alerts are available, but they operate as standalone features rather than an integrated system. This leaves customers to manually interpret dashboards, anticipate sequencing risks, and independently evaluate credit options when shortfalls emerge. The current approach reacts at the moment of failure rather than providing context-aware guidance before problems occur. This creates two fundamentally different scenarios that are unfortunately conflated in the customer experience: payment orchestration risk, where funds exist but system timing causes failure, and short-duration liquidity risk, where funds are genuinely unavailable within a narrow processing window. Today, both states trigger the same blunt response of a low balance notification followed by generic credit visibility or post-failure explanations.

What customers need is not simply more alerts, but clarity that accounts for the difference between timing risk and genuine shortfall—and guidance that arrives before the failure, not after

* 1. The Solution Gap

NAV»Money already detects when individual customers and SMEs are likely to enter short-term shortfall positions, based on cashflow patterns, upcoming debit obligations, and expected inflows. The bank therefore has visibility into liquidity risk before it materialises.

However, when these shortfalls occur, customers are typically presented with generic credit options (overdrafts, temporary loans, or facility increases) without contextual guidance on which option best fits their specific situation. These products are structurally sound, but they are not situationally intelligent. They are designed as standing facilities or broad liquidity tools, rather than responses tailored to a defined, time-bound shortfall event.

As a result, customers must independently evaluate complex trade-offs under time pressure: whether to allow a debit to fail, draw down on an overdraft, apply for new credit, or wait for incoming funds. This often leads to over-borrowing, incurring avoidable penalty fees, or entering facilities disproportionate to the duration and size of the gap.

For individuals, this can mean paying more in interest or merchant penalties than necessary, despite having predictable income inflows. For SMEs, even small shortfalls can disrupt payroll timing, supplier relationships, or service continuity, not because credit is unavailable, but because the most appropriate option is unclear at the moment it is needed.

The gap, therefore, is not the absence of credit mechanisms, but the absence of a decision intelligence layer that interprets shortfall context, repayment confidence, and product suitability and transparently recommends the most financially appropriate course of action.

## Solution

Debit order reminders sent through the FNB app (and later the FNB WhatsApp channel) and if FNB identifies that a customer is likely to have insufficient funds based on their spending patterns, the bank could proactively offer an overdraft facility. Customers would be able to apply directly through the app and receive timeously feedback before the debit order is processed, hence equipping customers to handle their finances more effectively.

## How does this solution benefit FNB?

By giving customers timely debit order reminders and providing them with a quick way to access a small overdraft when they are at risk of missing a payment, customers become more informed and better able to manage their finances. This support helps reduce failed debit orders and gives customers a better chance of maintaining a positive credit record. As their credit scores improve, they become eligible for additional credit products such as home loans and vehicle finance, which ultimately brings more business to FNB.

Furthermore, offering flexible repayment options—either upfront or in short-term installments—FNB can generate additional income from the associated interest on these overdraft repayments.

## Research

This section presents the empirical findings derived from the survey data collected to justify this study. The dataset, *Debit Order: The Early Bird That Took My Money.xlxs****,*** containts 29 complete responses and provides insights into customer experiences, challenges, and perceptions relating to the debit order processing. The findings directly support the identified problem space and validate the need for **Flowgaurd**, a predictive overdraft and debit-order intelligence system.

### 6.1 Prevalence of Debit order failures

Nearly half of respondents (48.3%) reported that they had experienced a debit order failing despite having planned adequately (“Yes”: 41.4%, “Maybe”: 6.9%) A further 41$ reporting experiencing failures “Rarely”, 17.2% “Sometimes, and 10.3% “Often”, indicating that debit order failures, while varying in frequency, are a persistent issue across the customer base.

This demonstrates that debit order failure is not an isolated pr0oblem but a common consumer experience requiring intervention.

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### 6.2 TIMING ISSUES AND Visibility GAPs

The survey revealed significant confusion and unpredictability around debit order timing:

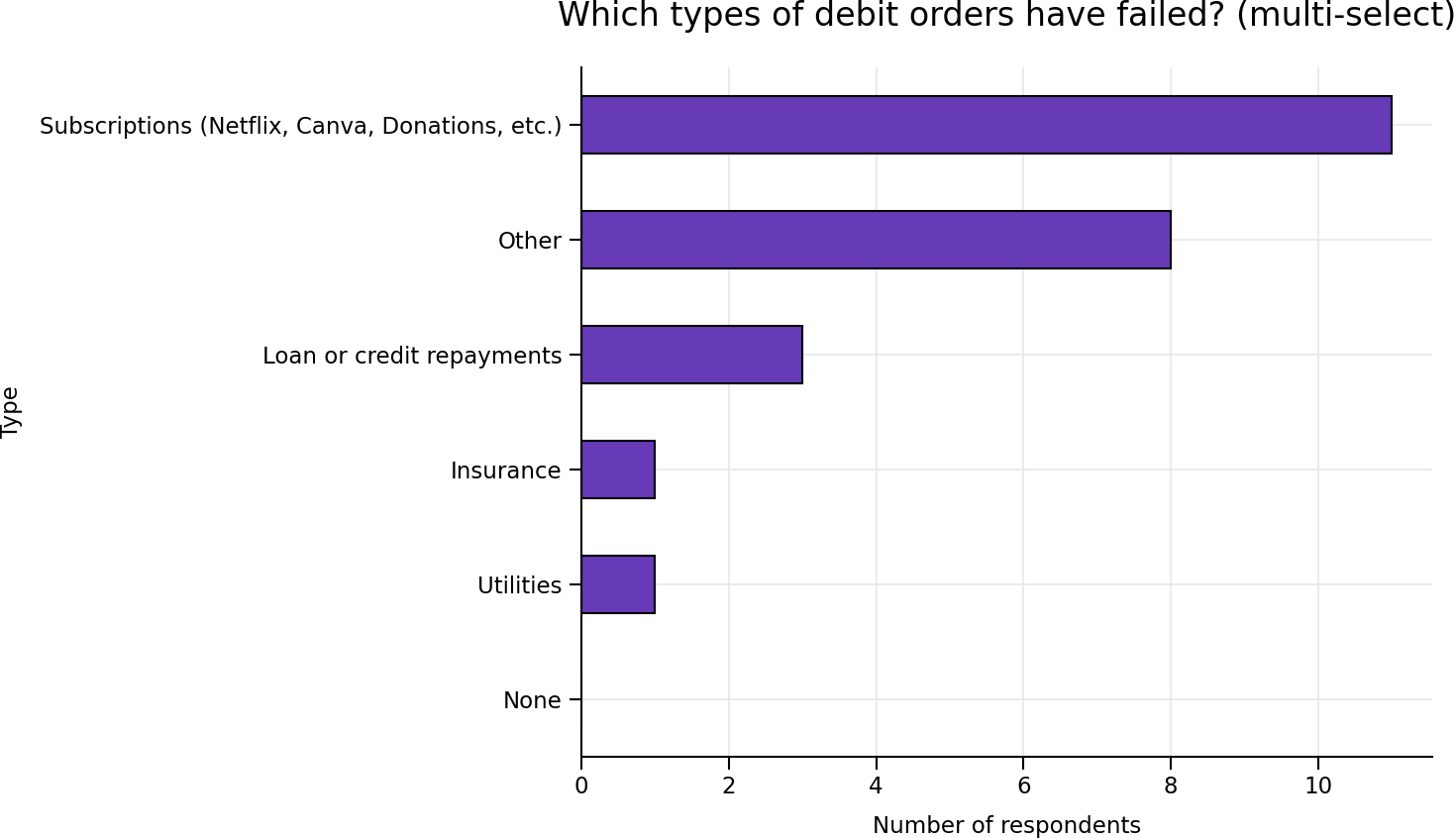
* **37.9%** of respondents indicated they are **caught off-guard** by debit orders going of when they don’t expect it.
* **31%** reported that debit orders sometimes go **earlier or out of sequence**.
* A combined **69%** of respondents either **do not understand** or are **uncertain** about why some debit orders go through and others do not.

Critically, visibility plays a substantial role in the customer experience. Among respondents who felt they did not have enough visibility, 66.7% were caught off guard by debit orders. IN contrast, only 15.4$ of those who felt they did have visibility experienced the same issue. This presents a 52-percent-point difference illustrating visibility as a key predictor of customer difficulties.

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### 6.3 Categories of debit orders most likely to fail

Multi-select analysis showed that the debit orders most prone to failure were:

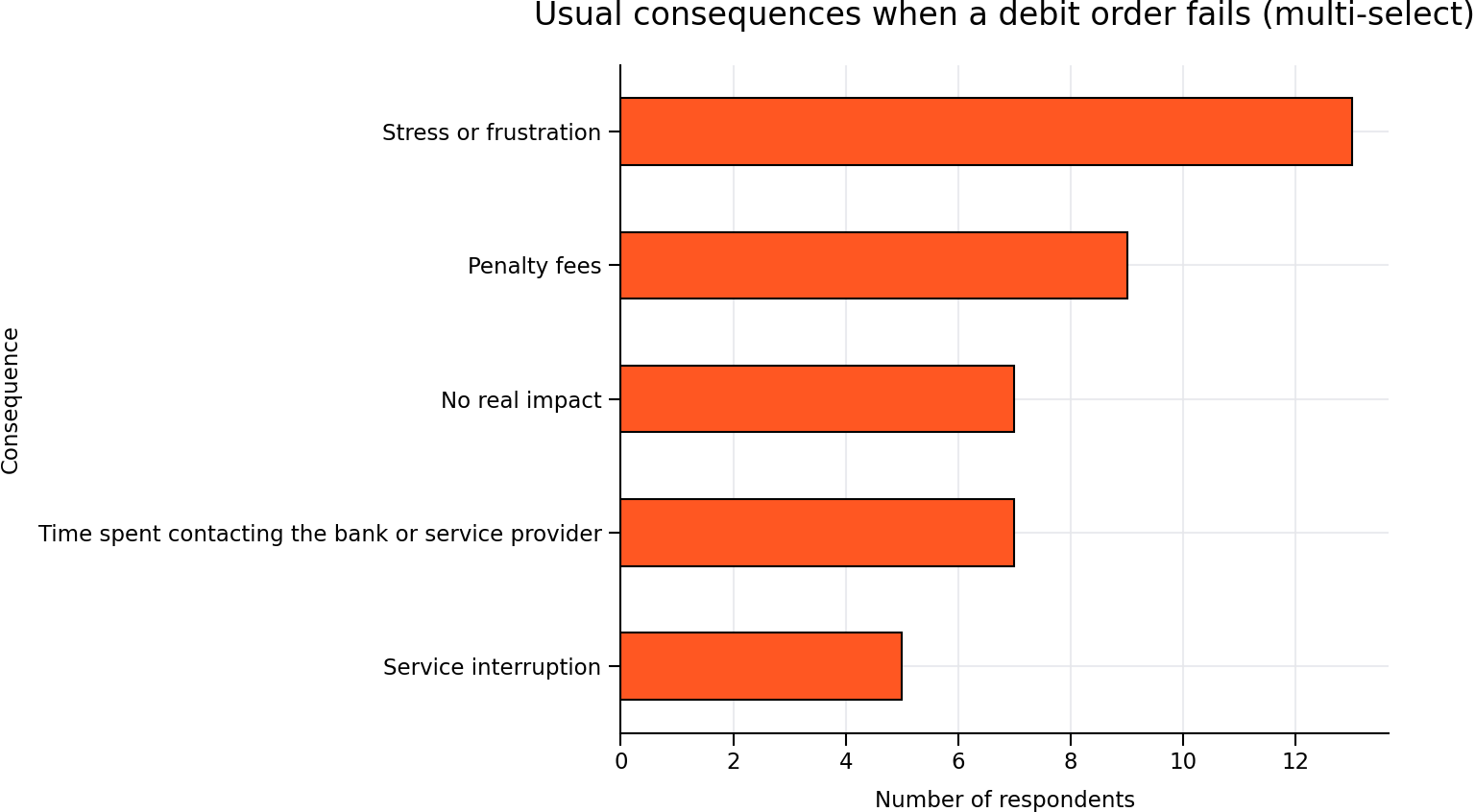
A bar chart with text

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Although respondents in the survey primarily associated missed debit orders with subscription services, a separate dataset of transaction‑level performance reveals that **Insurance (73.37% success rate)** and **Loan Repayments (79.20%)** are the most frequently missed debit orders in real-world processing. This discrepancy highlights a meaningful behavioural insight: consumers may underestimate failures in high‑value categories while more vividly recalling unsuccessful subscription payments.

### 6.4 Consequences of debit order failures

Participants reported experiencing multiple negative consequences following failed debit orders:



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Furthermore, respondents who reported a debit order “bouncing” due to insufficient funds had a **higher likelihood of incurring penalty fees (35.7%)** compared to those who did not experience a bounce (26.7%).

### 6.5 SATISFACTION WITH Bank support

Most respondents (**55.2%**) reported that they **do not feel supported** by their banks when debit orders fail, while only **20.7%** felt supported. Additionally, **20.7%** indicated that repeated failures negatively affect their perception of their bank, with **37.9%** unsure.

However, **86.2%** stated that **fewer unexpected debit order failures would improve their trust** in their bank, highlighting a meaningful opportunity for banks to restore customer confidence.

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### 6.6 DEMAND FOR A PREDICTIVE Debit-order system among fnb customers

To assess demand for a predictive debit‑order‑failure system specifically within **First National Bank (FNB)**’s customer base, survey responses regarding the usefulness of advance debit-order failure notifications were analysed alongside respondents’ primary banking affiliations.

Across the full sample, **86.2%** of respondents indicated that advance notice of a likely debit‑order failure would be useful, with only **3.4%** stating it would not be useful. When isolating responses by banking institution, a consistent pattern of strong demand emerges.

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**FNB Customer Group**

FNB represented the largest customer segment in the survey, with **11 respondents** identifying FNB as their primary bank (survey was random and not shared on any FNB associated groups). Within this group:

* 81.8% (9 out of 11) indicated that advance notification would be useful.
* The remaining respondents indicated “Maybe”, with no FNB customers rejecting the usefulness of such a service.

### **Comparative Insights Across Banks**

An analysis of all banks represented in the dataset shows that demand for predictive alerts is **consistently high regardless of banking institution**, but particularly pronounced among the major retail banks:

* Customers from **Absa, Capitec, Nedbank, and Standard Bank** all showed **100% usefulness agreement**, although sample sizes were smaller.
* FNB customers showed an **81.8% usefulness agreement**, the highest among banks with a substantial number of respondents (n=11).  
   (Based on the expanded bank‑response mapping from the dataset.

This strongly suggests that **FNB customers are just as motivated—if not more so—than other bank groups** to adopt a predictive debit‑order system.

### **Interpretation for FNB**

### Two insights are particularly relevant for positioning **Flowguard** within FNB:

* **High demand meets low awareness:**  
  Despite the high demand, **most respondents (58.6%) indicated that their bank does *not* currently offer such a service**, and a further **34.5% were unsure**. Only **6.9%** believed their bank offered predictive debit‑order support.  
   This suggests a substantial awareness gap and market opportunity for FNB to lead in this space.
* **FNB customers experience the same pain points:**  
  FNB respondents reported:
* Exposure to timing unpredictability
* Incidences of debit order failures
* Stress and frustration associated with failed debit orders  
   These trends mirror the broader sample, confirming that **FNB clients face the same systemic issues** and would benefit directly from predictive interventions.

### **Conclusion**

The combined analysis demonstrates that **FNB customers show a strong and quantifiable appetite for a predictive debit‑order‑failure system**, with more than four‑fifths expressing support for such functionality. Demand is aligned with broader trends across all banks, but FNB’s larger represented customer base provides clearer evidence of meaningful adoption potential.

This reinforces the strategic viability of implementing **Flowguard** within the FNB environment as a high‑impact, customer‑centric innovation capable of improving trust, reducing unexpected debit‑order failures, and delivering proactive financial guidance

## The FlowGaurd

Cashflow Assurance is a predictive financial layer that bridges the gap between customer intent and payment reality. It transforms reactive banking into proactive protection by continuously monitoring upcoming obligations, expected inflows, and real-time balance positions—distinguishing between timing risk, where funds exist but system friction causes failure, and genuine shortfall. Before a debit order fails, Cashflow Assurance simulates the impact of scheduled payments, surfaces upcoming commitments with clarity, and intervenes with contextual recommendations tailored to the specific gap, whether that means reshuffling payment timing, activating short-term liquidity, or accessing the most appropriate credit product.

What Cashflow Assurance is not is equally important. It is not simply another alert that waits for failure to explain what happened, nor is it a generic credit offer presented at the moment of stress. It is not a static dashboard requiring customers to manually connect dots between balances and dates, and it is not itself a credit product—it is a decision intelligence layer that interprets context and guides customers toward the most financially sound path. Critically, it is not one-size-fits-all: it accounts for the difference between a salaried individual with predictable inflows and an SME with irregular revenue cycles, tailoring guidance to the rhythm of each customer's financial life.

## Debit Order Assurance

The Debit Order Assurance Notification System introduces a push-based alert mechanism that supplements existing tracking features by notifying customers of upcoming financial commitments in advance of processing.

## Data Architecture

The system would employ a hybrid data model combining verified mandate information with predictive analytics:

### Mandated Obligations

The system would leverage existing DebiCheck and other approved debit order mandate data to deliver 100% accurate notifications for fixed bank-contracted payments. This ensures reliability for recurring obligations such as bond repayments, insurance premiums, and subscription services processed through formal mandate agreements.

### Predictive Analytics for Non-Mandated Payments

For recurring payments without formal mandates (such as third-party subscription services), the system would utilise historical transaction data already powering nav»Money functionality. By analysing three months of payment patterns, the system would be able to accurately identify and flag recurring obligations with high confidence.

## Notification Framework

### Timing and Customisation

Customers receive notifications two days before each debit order is scheduled to process. This default timing balances advance warning with relevance, while remaining fully customisable to individual preferences ranging from one to five days in advance.

### Delivery Channels

Notifications are to be delivered through multiple channels to ensure maximum reach and reliability:

* **Mobile banking app push notifications** - primary channel for app users integrated with InContact in-app notifications.
* **SMS** - backup channel and option for customers without the app
* **WhatsApp** - planned for future implementation on an opt-in basis

This multi-channel approach ensures customers receive timely alerts regardless of their preferred engagement method.

### Customer Impact

The notification system fundamentally shifts customer behaviour from reactive crisis management to intentional financial planning. By providing advance visibility of upcoming obligations, customers can proactively ensure sufficient funds are available, thereby avoiding failed payments, penalty fees, and credit score damage.

## Enhanced nav»Money Dashboard

### Upcoming Obligations View

It is proposed that a new section within nav»Money be added to provide customers with a consolidated list of all debit orders due. While debit order mandates are currently visible in the profile section of the mobile banking app, this enhanced view delivers a contextual, action-oriented presentation specifically designed for cashflow management and budgeting purposes.

### Dashboard Capabilities

From the nav>>Debit Orders page, customers can:

* **Customise notification timing** for individual debit orders. For example, five days' notice for rent or mortgage payments and one day for entertainment subscriptions
* **The ability to toggle notifications on or off** for specific obligations based on personal preference
* **View projected balance impact** showing whether customers would have a shortfall to cover the upcoming debits.
* **The ability to take immediate action** if they are in a shortfall, by applying for a buffer to cover the upcoming obligations.

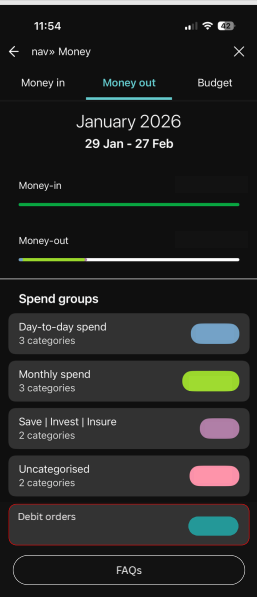
## Competitor Analysis

A competitor analysis was conducted to assess how major banks competing with FNB integrate their money management (MM) tools with transaction notification systems, with a particular emphasis on pre-emptive debit order alerts. The objective is to understand how effectively each institution enables customers to proactively manage their finances through a combination of predictive insights, budgeting capabilities, and real-time alerts. By examining the functionality, strengths, and shortcomings across these competitors, this analysis highlights areas where FNB maintains a competitive advantage, as well as opportunities for enhancement. These insights ultimately support FNB in strengthening customer financial awareness and driving deeper engagement with existing products

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Bank | Money Management (MM) Tool | MM Tool Overview | Transaction Notification System | Predictive Debit Order Alerts‑Order Alerts | Distinguishing MM or Notification Feature | Gaps |
| FNB | **nav>>Money** | Tracks & categorises spend; supports auto & manual budgets; predicts safetospend and month end balances‑to‑spend and month‑end balances | **InContact** – SMS & in-app alerts for real-time transactions, with account balances included‑app alerts‑time | **No** - real-time only‑time only | Predictive balance forecasting that can factor in future payments like debit orders and recurring commitments | Missing an awareness / proactive element; users must constantly manually check dashboards to stay ahead |
| Discovery Bank | **Financial Analyser** | Categorises spend; supports manual & automated budgets; limited predictive financial insights | Email & in-app alerts for real-time transactions, with account balances included‑app alerts‑time | **Yes –** Mandated debit orders | Offers multiple debit order alerts that notify users of upcoming debit amounts and account balances before debits‑order alerts that notify users of upcoming debit amounts and | Missing deeper predictive budgeting and cash‑flow projections |
| Capitec | **None** | Not Applicable | SMS alerts for real-time transactions.‑time | **No** - real-time only‑time only | None identified | Overall, lacks money management insights. |
| ABSA | **ABSA Savings Coach** | Personalised goals that rewards achieving said goals. Autosaver tool that saves money from each transaction. No extra costs. Tracks progress. | **NotifyMe** – SMS, email & in-app alerts for real-time transactions, with account balances included app alerts time ‑app alerts‑time | **No** - real-time only‑time only | Users can opt‑in for daily or weekly balance updates |  |
| Standard Bank | **Money Movements, Future Payments & Budget Manager** | Tracks spend & inflows; supports manual budgeting; shows expected payments over 14‑ and 30‑day periods | **MyUpdates** – SMS & in-app alerts for real-time transactions, with account balances included‑app alerts‑time | **No** - real-time only | Dashboard surfaces expected payments at multiple levels (summary totals to individual upcoming payments) | Predictive dashboard requires manual addition and lacks visibility. Users are not pushed with proactive notifications |
| Nedbank | **MoneyTracker** | Tracks spend & inflows; supports manual budgets; no predictive forecasting | SMS & in-app alerts for real-time transactionsapp alerts time ‑app alerts‑time | **Unclear** | None identified | Missing predictive MM elements and notification features |

From the competitive landscape, it is evident that FNB leads in predictive budgeting through features such as ‘My Available Funds’, which incorporates expected payments into a customer’s projected balance. However, the transparency behind which payments are included in this calculation is limited. In contrast, Standard Bank’s Future Payments feature offers strong visibility into upcoming transactions, presenting them clearly even though it lacks FNB’s predictive balance capability. Additionally, introducing features like Discovery Bank’s proactive debitorder notifications could further enhance the nav>>Money experience and significantly strengthen FNB’s position in empowering customers with timely, actionable financial insights. Order‑ notifications could further enhance the nav>>Money experience and significantly strengthen FNB’s position in empowering customers with timely, actionable financial insights.

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## Contextual Credit Engine (CCE) (Component 2)

The Contextual Credit Engine (CCE) is a decision-intelligence layer designed to optimise credit guidance at the precise moment a shortfall is predicted. It forms the second core component of the Paysure proposition, operating downstream of Debit Assurance and upstream of customer action. Where Debit Assurance addresses payment orchestration risk—ensuring that existing funds are marshalled effectively across timing frictions—the CCE addresses short-duration liquidity risk: genuine funding gaps that require financing to prevent payment failure.

Unlike traditional credit decision systems, which assess eligibility in isolation, the CCE evaluates credit suitability within a defined event context: a specific upcoming obligation, a quantified shortfall amount, and a measurable recovery window. Its purpose is not to originate new credit products or expand balance sheet exposure indiscriminately. Rather, it leverages existing FNB credit facilities and matches them intelligently to short-duration liquidity events. In doing so, it transforms credit from a static facility into a situationally optimised tool. The engine sits downstream of NAV»Money's shortfall detection capability and upstream of customer interface guidance, bridging predictive visibility with responsible credit pathing.

## Architectural Position Within the Ecosystem

The CCE integrates four core capability layers already present within FNB:

* **Predictive Cashflow Modelling** – detects upcoming shortfalls based on expected inflows and scheduled debits
* **Credit Infrastructure** – overdrafts, temporary loans, credit cards, facility increases
* **Risk and Affordability Frameworks** – internal behavioural scoring and affordability models
* **Customer Interface Layer** – app-based guidance and simulations

Rather than replacing these systems, the CCE orchestrates them. Where traditional credit decisioning answers the question of whether a customer is eligible for a given product, the CCE answers a fundamentally different question:

“Given this specific shortfall event, which available facility results in the lowest cost, lowest risk, and highest repayment certainty?”

This shift from product-centric eligibility to context-centric optimisation is the defining innovation.

## Modelling Framework

The CCE operates on a three-stage modelling structure.

Stage 1: Event Classification Model

In the first stage, the engine determines the nature of the predicted shortfall before any credit comparison occurs. It classifies the shortfall into one of two primary categories:

|  |  |
| --- | --- |
| Classification | Description |
| Payment Orchestration Risk | Funds exist within a near-term window, but sequencing or settlement mechanics create a temporary deficit |
| Short-Duration Liquidity Risk | Funds are genuinely unavailable within the debit processing window, requiring financing to prevent failure |

This classification is critical because it determines whether credit guidance is appropriate at all. If orchestration risk can be resolved through Debit Assurance mechanisms alone, credit recommendation is suppressed. The classification model draws on expected inflow timestamp proximity, historical income consistency, past shortfall duration patterns, mandate retry behaviour, and balance volatility metrics. Only when liquidity risk is confirmed does the engine progress to product comparison.

Stage 2: Repayment Certainty Assessment

In the second stage, the CCE calculates a Repayment Certainty Index (RCI) for the defined exposure window once liquidity need is validated. Unlike traditional credit scoring, which evaluates long-term default probability, the RCI focuses on short-horizon recovery likelihood. It synthesises the following inputs:

|  |  |
| --- | --- |
| Input Variable | Description |
| **Income stability score** | Coefficient of variation of net monthly inflows over a rolling window |
| **Historical short-term credit repayment performance** | Proportion of short-term facilities repaid within agreed terms |
| **Debit order success ratio** | Proportion of scheduled debits successfully honoured over a rolling period |
| **Overdraft utilisation discipline** | Average utilisation as percentage of limit; frequency of excesses |
| **Savings buffer ratio** | Average available balance relative to monthly outflow volatility |

The RCI outputs a probability-weighted recovery confidence score over the specific shortfall duration, whether three days, seven days, or fourteen days. Tier segmentation guides decisioning as follows:

|  |  |  |
| --- | --- | --- |
| **RCI Tier** | **Score Range** | **Credit Decisioning** |
| **Tier 1** | ≥ 0.85 | Full credit options available |
| **Tier 2** | 0.70 – 0.85 | Core credit options available |
| **Tier 3** | 0.55 – 0.70 | Restricted options, higher scrutiny |
| **Tier 4** | < 0.55 | Credit suppressed; alternative guidance provided |

This ensures that the engine does not recommend facilities where repayment timing confidence is weak.

The CCE includes embedded guardrails to ensure responsible operation:

| **Safeguard** | **Function** |
| --- | --- |
| **Repeated shortfall detection** | Triggers structural review rather than continued liquidity guidance |
| **Low RCI tiers** | Suppress high-risk facility recommendations |
| **Duration thresholds** | Prevent long-term compounding risk |
| **High-frequency usage flags** | Signal possible affordability deterioration |

Together, these safeguards ensure the engine remains corrective rather than enabling, supporting customers through temporary gaps while protecting them from structural over-reliance.

Stage 3: Contextual Product Optimisation Model

In the third stage, the engine performs a comparative analysis. For each eligible facility available to the customer, it simulates the required draw amount, expected utilisation duration, applicable interest rate, fee structure including initiation, monthly, and penalty risk, compounding risk, early repayment cost, and a behavioural risk premium based on the RCI tier.

The engine then calculates the Total Cost of Liquidity (TCL) over the predicted usage window as:

TCL = Interest Accrued + Applicable Fees + Risk Adjustment Factor

To incorporate repayment uncertainty, it computes the Risk-Adjusted Liquidity Cost (RALC):

RALC = TCL + ϕ · (1 - RCI) · S · LGD

Where;

ϕ = risk-weight parameter reflecting capital cost,

S = shortfall magnitude, and LGD is loss given default for the facility type.

Each facility receives a contextual suitability score based on lowest total projected cost, highest repayment certainty alignment, lowest behavioural risk amplification, and minimal long-term facility dependency. The facility with the optimal combined score becomes the recommended path.

A behavioural dependency penalty is applied to prevent structural overuse:

DP = κ · max(0, U - μ\_U)

Where;

U = shortfall usage frequency over a rolling window,

μ\_U = acceptable behavioural threshold initially calibrated at three events over ninety days.

κ = penalty coefficient calibrated to offset the customer benefit of repeated usage.

The final optimisation objective selects the facility that minimises the sum of the Risk-Adjusted Liquidity Cost and this dependency penalty.

For completeness, the formal optimisation problem can be stated as follows.

Given a predicted shortfall event at time(tᵢ) with magnitude(S) and recovery horizon(ΔT), and given a set of available facilities(F), the CCE selects f∗ ∈ F that minimises:

f∗ = argmin [ (S · r\_f · ΔT/365 + c\_f) + ϕ · (1 - RCI) · S · LGD\_f + κ · max(0, U - μ\_U) ]

subject to facility limit constraints, tier-appropriate RCI thresholds, and behavioural guardrails on usage frequency. The engine exposes the decomposition of this calculation to the customer interface, enabling transparent explanations such as comparative cost breakdowns over the relevant duration and repayment confidence estimates based on observed income patterns.

## Credit Facilities Utiliised

The table below summarises the optimal use cases for each facility type:

|  |  |  |
| --- | --- | --- |
| **Facility** | **Optimal Use Case** | **Rationale** |
| **Overdraft** | Very short duration gaps (1–5 days); customers with strong RCI scores; low draw amounts relative to income | Immediate liquidity; no new application friction; typically, lowest cost for short horizons |
| **Credit Card Utilisation** | Customers with unused credit limits; merchant-specific debit obligations; short-cycle repayment confidence | Interest-free period where applicable; no additional facility activation; repayment flexibility |
| **Temporary Loan** | Larger shortfalls; lower RCI tiers; shortfalls exceeding typical overdraft duration | Fixed repayment terms; predictable cost structure; reduced compounding uncertainty |
| **Facility Increase** | Strong behavioural history; structural recurring misalignment; usage pattern justifies permanent limit adjustment | Recommended conservatively to avoid long-term dependency creation |

The CCE transforms FNB's existing predictive capability into contextual financial intelligence. Competitors may offer alerts, budgeting tools, or credit products, but few integrate predictive shortfall detection with comparative credit optimisation in real time. The CCE therefore positions FNB not merely as a credit provider but as a liquidity decision partner. This moves the bank from reactive product distribution to proactive financial guidance, a distinction competitors cannot easily replicate without comparable predictive infrastructure.

Within the Paysure proposition, the CCE completes the arc: Debit Assurance prevents failures where funds exist but timing falters, while the CCE intelligently bridges genuine gaps where funds are absent but intent remains. Together, they form a unified layer that protects customers from the hidden failures of everyday banking.

## Abuse & Risk Pressure Testing

Any system that influences financial behaviour must be tested not only for its intended effects, but for how it behaves under pressure. The Contextual Credit Engine operates at the intersection of human behaviour, market dynamics, and macroeconomic forces. This section examines the key risks that could challenge its performance and the safeguards that keep it resilient.

## Behavioural Gaming

Customers learn how the system works and adapt. They might temporarily inflate balances before debits, repeatedly rely on short-term funding, or time transactions to access lower-cost facilities. These behaviours are economically rational, not malicious, but they distort the engine's signals.

**The risk scenario.**

A customer shifts funds in before debit processing and out again afterward, repeatedly triggering the lowest-cost recommendation. The system rewards short-term manipulation rather than genuine financial health.

**The safeguard.**

The CCE evaluates pattern stability, not isolated events. Abrupt balance changes and repeated micro-shortfalls reduce repayment confidence scores dynamically. If a customer triggers contextual funding too frequently, the engine shifts from short-term recommendations to structural intervention, such as affordability review. The goal is not to deny liquidity, but to prevent dependency loops.

## Dependency and Conduct Risk

If the engine consistently rescues customers from shortfalls, they may begin to treat contextual liquidity as part of their expected balance. This invisible credit creep reduces financial discipline and increases long-term risk exposure.

**The risk scenario.**

A customer relies on contextual funding for small gaps every month, never noticing the cumulative cost or recognising that their cashflow pattern signals a deeper problem.

**The safeguard.**

The CCE requires explicit cost comparison before any credit activation. It shows cumulative usage over rolling periods. It introduces graduated friction after repeated reliance. And it maintains a clear distinction between timing mismatches, where funds exist, and genuine affordability gaps, where they do not. This prevents the engine from masking structural stress with repeated micro-interventions.

## Correlated Liquidity Stress

Shortfalls cluster around month-end, seasonal spikes, and economic shocks. If thousands of customers trigger contextual funding simultaneously, the engine becomes a large-scale short-term funding channel, straining liquidity buffers.

**The risk scenario.**

A month-end confluence of salary delays and high debit volumes sees twenty percent of eligible customers trigger funding at once. Portfolio exposure spikes faster than anticipated.

**The safeguard.**

The CCE operates under dynamic portfolio constraints. During systemic stress, repayment thresholds rise, funding limits compress, and preference shifts toward facilities already capitalised, such as approved overdrafts. The engine expands in stable environments and tightens under pressure, aligning with prudential risk principles.

## Macroeconomic Shock

Models built on historical data fail during structural breaks. A recession changes income patterns, recovery rates, and default correlation. The engine cannot assume the past will repeat.

**The risk scenario.**

A recession hits. Customers with previously stable incomes experience irregular salaries. The engine, calibrated on pre-recession data, continues recommending credit that customers can no longer reliably service.

**The safeguard.**

The CCE monitors unemployment trends, sector volatility, and portfolio-level repayment slippage. When indicators signal deterioration, confidence weightings adjust downward. Stress testing simulates delayed salaries, elevated retry failures, and increased penalty propagation. The goal is to understand how quickly expected loss expands under pressure, not to pretend it won't.

## Model Drift

Payment systems evolve. Retry logic changes. Customer behaviour shifts. A model calibrated on last year's patterns quietly degrades.

**The risk scenario.**

A change in industry retry windows means debits now retry two days later. The engine, unaware, continues recommending one-day facilities, and customers face unexpected second-day shortfalls.

**The safeguard.**

The CCE continuously backtests against realised outcomes, monitors prediction error dispersion, and recalibrates regularly. Qualitative review complements quantitative monitoring: if customer support tickets spike around specific recommendations, model assumptions are interrogated. Automation without governance is fragility.

## Fraud and Malicious Abuse

While most risks are behavioural, not criminal, malicious patterns remain possible: coordinated inflow cycling, synthetic accounts built to trigger credit, rapid abandonment after drawdown.

**The risk scenario.**

A group opens multiple accounts, cycles small amounts to establish apparent income patterns, draws contextual credit across all accounts simultaneously, and abandons them.

**The safeguard.**

The CCE integrates with the bank's fraud detection systems. It consumes fraud risk signals in real time and suppresses recommendations in high-risk environments. Liquidity features cannot become low-friction exploitation channels.

## Ethical and Reputational Safeguards

If the engine appears to prioritise fee extraction over customer stability, or to penalise vulnerable customers disproportionately, it undermines its strategic purpose. Credibility depends on perceived fairness.

**The risk scenario.**

A customer with irregular income repeatedly triggers funding. The engine recommends the lowest-cost option each time but never signals that their pattern warrants a broader conversation about affordability.

**The safeguard.**

In timing-risk scenarios, where funds exist but timing fails, costs are minimised. In affordability-risk scenarios, where repeated shortfalls signal structural stress, escalation to advisory support is available. A mathematically optimal recommendation that feels unfair erodes trust. A transparent recommendation, even at slightly higher cost, builds it.

# 02

## Financial & Strategic Impact

This section quantifies Flowguard’s potential to avoid costs, protect/expand revenue, and keep balance-sheet exposure tight using only bank-wide debit-order volumes and outcomes from the *Overall Volumes incl Insure* that can be found in data provided by team members of debit-order related BUs.

### 10.1 WHAT THE OPERATIONAL BASE LOOKS LIKE (Bank-wide)

**Cumulative (2024/04 - 2026/01)**

|  |  |
| --- | --- |
| **Submitted Debit Orders** | 233,211,673 |
| **Successful Debit Orders** | 187,642,515 |
| **Overall Success Rate** | 80.46% --> Implied 19.54% failure rate |

**By Channel (Cumulative)**

|  |  |  |  |
| --- | --- | --- | --- |
| **Channel** | **Submitted** | **Successful** | **Rate** |
| **DC (DebiCheck)** | 85,431,900 | 75,131,922 | 87.94% |
| **EFT** | 145,888,796 | 111,094,059 | 76.15% |
| **RM (Registered Mandate)** | 1,890,977 | 1,416,534 | 74.91% |

**Interpretation:** EFT carries the **largest volume and the largest absolute failure count;** it’s the **first place to hunt** for avoided failures and revenue protection. **Note:** Registered mandates have only been around since 2025/06.

## 10.2 COST Avoidance

|  |  |  |  |
| --- | --- | --- | --- |
| Segment (2025/01 - 2026/01) | Current Failures | 1% fewer | 3% fewer |
| Total (All channels) | 12,293,780 | 122,938 | 368,813 |
| DC | 2,404,484 | 24,045 | 72,135 |
| EFT | 9,426,499 | 94,265 | 282,795 |
| RM | 462,797 | 4,628 | 13,884 |

**Cost attachment formula:**

|  |
| --- |
| Cost\_Avoided (R)  = Avoided\_Failures × [Avg Penalty Fee per fail (R)]  + Avoided\_Failures × [Avg Call/Back-office Cost (R)] × [% of fails escalating]  + Avoided\_Failures × [Avg Reinstatement/Admin Cost (R)] × [% of impacted services] |

**Tip:** If Finance wants the **fastest quantified win**, price the EFT rows first; that’s where most savings will materialise.

## 10.3 REVENUE GENERATION (PREDICTIVE OVERDRAFT & Cashflow PROTECTION)

Flowguard monetises **at the moment of need** when a shortfall is predicted for a specific upcoming debit (or any other cashflow related issue).

|  |
| --- |
| Overdraft\_Revenue (R)  = [Avoided\_Failures\_funded]  × [Avg Top-up Amount (R)]  × [Avg Utilisation Days / 365]  × [Effective Annual Rate] |

Where

* **Avoided\_Failures\_funded** = Avoided\_Failures × [% of customers who accept the funding option]
* **Effective Annual Rate =** applicable interest (and appliable fees) net of waivers

## 10.4 Revenue protected from successful collections

Every avoided failure also **protects** the underlying product revenue (premiums, repayments, subscription-linked fees).

|  |
| --- |
| Revenue\_Protected (R)  = Avoided\_Failures × [Avg Debit Amount (R)] × [Product Margin %] |

## 10.5 BALANCE SHEET EXPOSURE (TIME-Bound, capped)

Flowguard is designed to **minimise risk** by matching credit to verified, near‑term debit needs:

* **Time‑bound exposure** — top‑ups typically last **24–72 hours** until the debit clears.
* **Capped amounts** — limited to the **specific shortfall** (not full facility drawdowns).
* **Policy limits by channel/merchant** — prioritise high‑volume EFT flows first to maximise ROI without expanding risk footprint.

**Exposure monitoring template:**

|  |
| --- |
| EAD\_Flowguard (R)  = Σ [Top-up Amount\_i × (Avg Days Outstanding\_i / 365)] |

## Competitive and strategic positioning

This section outlines why Flowguard works uniquely well in FNB’s ecosystem because it relies on deep internal data—like customer cash‑flow patterns, debit‑order timing, and credit‑behaviour signals—that only FNB can see and model accurately. Competitors may copy the idea, but they can’t replicate the underlying prediction engine, because their MM tools are surface‑level and lack the integrated forecasting, alerting, and credit‑pathing capabilities FNB already has. By solving a major customer pain point proactively, Flowguard creates a level of daily usefulness that strengthens loyalty and makes FNB significantly harder to replace.

## 11.1 Flowguard relies on data that only FNB has

Flowguard needs deep, fine-grained visibility into:

* Customers' daily cash-flow patterns
* Debit-order timing across rails
* Balance trajectories and volatility
* Salary deposits and spending patterns
* Credit facility utilisation

These signals live inside FNB’s core ecosystem.

Because the model learns from *FNB-specific* behaviour, accuracy is tied directly to FNB’s environment.

Competitors cannot access our behavioural data, so even if they copy the concept, they cannot directly copy the capability.

## 11.2 FNB ALREADY HAS THE BUILDING BLOCKS – THE PRODUCT FITS NATURALLY

FNB has:

* **InContact** (real-time alerts)
* **Nav>>Money** (Budgeting + My Available Funds)
* **Rich transactional history**
* **Credit rails (temp loans, overdrafts, credit card)**
* **Advanced internal data science infrastructure**

Flowguard uses all four in one integrated loop:

In the case of debit orders: **Predicts debit-order risk --> alerts the customer --> offer right funding option --> ensures debit order success.**

No other bank has this combination of forecasting + alerting + credit rails already working together.

## 11.3 OTHER BANKS FOCUS ON VISIBILITY, NOT PREDICTION

Flowguard builds on FNB’s already strong money‑management ecosystem by adding a predictive layer that anticipates debit‑order risks before they happen, turning existing tools like My Available Funds and InContact into a proactive safety net. By integrating debit‑order forecasting with real‑time alerts and seamless access to funding options, FNB can offer customers a more complete and empowered way to manage their cashflow. This added predictive intelligence elevates the overall banking experience, making FNB even more indispensable in customers’ daily financial routines.

## 11.4 FLOWGUARD CREATES Ecosystem LOCK-IN THROUGH Usefulness – NOT Stickiness

Once customers experience:

* early warnings of upcoming failures
* predicted future balances
* personalised credit paths at the moment of need

Flowguard becomes something they **depend on**, not something they “check”.

A customer who avoids fees, stress, and failed debit orders **because of FNB** becomes significantly less likely to leave, because the benefit is tied to:

* their FNB income behaviour
* their FNB debit‑order patterns
* their FNB credit products
* their FNB notification stream
* their FNB cash‑flow data

None of this transfer cleanly if they move banks.

## 11.5 Competitors CAN COPY THE Idea, but not the execution

They would need to rebuild:

* predictive balance modelling
* debit-order risk scoring
* real-time shortfall simulation
* credit decisioning integration
* notification‑system integration
* risk and affordability guardrails

These require years of internal data, regulatory alignment, and system redesign. In practice, most banks struggle just to unify their MM tools and notifications. Flowguard is a **multi‑layer system**, not a feature.

# 03

## roadmap

Phased rollout:

* Phase 1
* Phase 2
* Phase 3

Include:

* What is reused
* What is new

## SUCCESS metric

Prove how we know it worked.

* Predictive Overdraft utilisation vs repayment rate
* Reduction in debit order failures
* Reduction in involuntary churn

# APPENDIX A

A.1 OVERVIEW

## A.2 Initial Brainstorming & Exploration

Our process began with a comprehensive audit of FNB’s customer touchpoints, ranging from mobile and online banking to physical branches, ATMs, and backend systems. By casting a wide net across these diverse domains, we aimed to surface high-impact opportunities before narrowing our focus to the most critical pain points. Through this discovery phase, we determined that all identified challenges converged into three areas: Security, Operations, and Cash Flow Management.

|  |
| --- |
| **DOMAIN 1: Security** |
| **Ideas Explored:**  • **Prepaid Accounts:** Virtual cards linked to prepaid accounts for additional fraud protection and possible budgeting use.  • **Session Management:** Auto-logout when phone is locked to prevent unauthorised access |

|  |
| --- |
| **DOMAIN 2: Operations** |
| **Ideas Explored:**  • **Customer Effort Index:** Identify high-friction touchpoints across FNB’s banking channels and measure task difficulty through analytics.  • **Rural ATM Access:** Expand infrastructure for cash deposits in underserved areas |

|  |
| --- |
| **DOMAIN 3: Cash Flow Management** |
| **Ideas Explored:**  • **Proactive Notifications:** Alerts customers 2-3 days before debit orders due  • **Predictive Overdraft:** Machine learning model predicting shortfalls and offering tailored short-term overdraft cover |

## a.3 Impact Matrix & Prioritisation

To prioritise which domain to pursue, we developed a decision matrix evaluating each domain against seven criteria areas, which can be found in Table

|  |  |  |  |
| --- | --- | --- | --- |
| **Evaluation Criteria** | **Domain 1: Security** | **Domain 2: Operations** | **Domain 3: Cash Flow** |
| **Customer Breadth** | **Low-Medium** | **Low-Medium** | **High** |
| **Financial Impact** | **Low**  **Potential fraud (rare)** | **Low-Medium**  **Indirect costs** | **High** |
| **Implementation Complexity** | **Low**  **App-only changes** | **High**  **Physical infrastructure or complex backend processes** | **Medium-High**  **App and backend changes** |
| **Time to Value** | **Fast** | **Slow** | **Moderate** |
| **Measurability** | **Medium**  **Fraud incident tracking** | **Low**  **Difficult attribution** | **High**  **Clear transaction data** |
| **Problem Classification** | **Bug/Feature**  **Technical fixes and minor feature additions** | **Infrastructure**  **Capital and Resource Investment** | **Experience Design**  **Systemic journey** |
| **Revenue Impact** | **Neutral**  **No revenue loss** | **Unknown**  **Indirect benefits** | **Negative**  **Loss of income from penalty fees** |
| **Weighted Score** | **12/21** | **10/21** | **17/21** |

|  |  |  |  |
| --- | --- | --- | --- |
| **Key: Colour and Associated Score** | **1** | **2** | **3** |

A.3.1 DISCUSSION

Using the impact matrix to refine our problem focus area, we identified several topics that did not warrant further customer engagement. These areas were deprioritised because they lacked sufficient impact, relevance, or alignment with strategic objectives.

**PREPAID DIGITAL CARD**  
This would be a product feature addition addressing customer anxiety around security and spending control. Existing workarounds exists, such as having dedicated virtual cards for various spend areas with unique limits attached to each. The virtual cards also provide adequate security using dynamic CVVs. This area would be a niche use case affecting a limited customer segment.

**SESSION MANAGEMENT**   
This is a security vulnerability requiring engineering remediation and does not directly affect customer engagement. This issue would likely have a low incidence rate and requires a binary solution which has limited strategic value.

**RURAL CASH DEPOSITS**  
An infrastructure challenge requiring substantial capital investment and the solution complexity extends beyond customer engagement optimisation and primarily serves a niche rural segment.

**CUSTOMER EFFORT INDEX (CEI)**  
The diagnostic framework would identify friction points but does not constitute a tangible customer deliverable. The CEI functions as a measurement tool rather than a solution in itself and would require subsequent interventions to address identified issues.

SELECTED PRIORITY AREA: CASH FLOW MANAGEMENT

Cash flow management emerged as the clear strategic priority based on four reasons:

* Customers experience this pain point daily rather than hypothetically. Unlike future benefits, like enhanced security, or abstract improvements, cash flow shortfalls and failed debit orders represent an immediate, tangible problem causing financial stress in real time.
* Improving cash flow management and reducing failed debit order would have a far wider reach than the use cases addressed by alternative domains.
* The average overdraft fee multiplied by monthly occurrence frequency represents a measurable, recurring financial burden directly impacting customer wellbeing. Unlike abstract efficiency gains or potential fraud losses, this constitutes real money leaving customer accounts every month.
* There is comprehensive transaction data that can provide clear baseline metrics including overdraft frequency, fee revenue, and timing patterns. Success can be measured objectively through reduction in overdraft incidents, decrease in fees paid, and improvement in nav»Money engagement metrics.