

A Comparative Qualitative Analysis of Managerial Cognitive Biases and Decision Inefficiency in Micro-enterprises: Evidence From a Process-Oriented Experiment

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This study examines the occurrence of cognitive biases in the operational decision-making of micro-enterprises using a comparative experiment. By comparing and analysing the operational “footprints” of two technologically matched vending machines, one managed by human intuition and the other by a simple, deterministic set of rules, we identify fundamentally distinct behavioural archetypes in decision-making. The human-managed case exhibited patterns of anchored adjustment, situational filtering, and outcome-sensitive volatile learning. In contrast, the rule-managed case demonstrated mechanical rigidity and contextual blindness, but also remarkable stability. The systematic divergence in their operational pathways, particularly in response to predictable events, provides process-based evidence that cognitive biases are not merely statistical correlates, but actual enacting and structuring forces that can lead to decision inefficiencies over time. We conclude that for micro-enterprises, improving decision quality may depend less on acquiring more data and more on structuring decision processes to mitigate the inherent instability of intuitive judgment.

Keywords: managerial cognitive biases, micro-enterprises, qualitative experiment, operations management, decision archetypes

Introduction

The persistent and disproportionately high failure rate of micro-enterprises remains a major puzzle in the economic development and entrepreneurship literature (e.g., Storey, 1994; Stam & Van Stel, 2011). These entities, which have been widely celebrated as engines of innovation and local economic vitality, face stubbornly low survival odds despite various forms of policy and financial support (Calcagnini & Favaretto, 2011). Conventional financial and strategic frameworks, which work well for analysing large corporations, struggle to explain the poor investment and operational decisions made in these owner-managed ventures. The canonical agency theory, which attributes investment inefficiencies primarily to misaligned interests between principals (owners) and agents (managers) (Jensen & Meckling, 1976), is a powerful framework for explaining organisational dysfunctions in large companies. However, its explanatory power is severely, if not entirely, diminished in the context of traditional micro-enterprises. Here, ownership and control are typically unified, with the entrepreneur serving simultaneously as the visionary and the day-to-day operator. This unification

ostensibly minimises, if not eliminates, classical agency costs arising from goal divergence. Yet micro-enterprises continue to experience high failure rates, poor capital allocation, and operational missteps that far exceed what agency theory can explain. This glaring theoretical gap compels scholarly inquiry into a different domain: the internal cognitive world of the individual decision-maker, who bears sole responsibility for all strategic and tactical decisions.

Over the past few decades, the field of behavioural economics and finance has rigorously established that systematic cognitive deviations from neoclassical rationality (collectively termed cognitive biases) are significant and often the primary causes of corporate investment distortions and market anomalies (Malmendier & Tate, 2005; Baker & Wurgler, 2013; Shefrin, 2018). Grounded in Kahneman and Tversky's (1979) groundbreaking work on prospect theory and heuristics, this paradigm shift recognises that decision-makers are not coldly rational optimisers, but "affect-rich", intuition-driven individuals subject to predictable mental shortcuts. However, a critical review of the existing empirical literature reveals a significant contextual bias: It overwhelmingly focuses on large, publicly traded corporations. Researchers in this field frequently rely on clever but indirect proxies for cognitive biases, such as the tone of CEO media coverage, the timing of stock option exercises, or corporate acquisition decisions (e.g., Baker & Nofsinger, 2010). Consequently, while we have a good understanding of how biases operate in the boardrooms of big business, there is a profound lack of knowledge about how these same biases function in the "pure", high-stakes, and intensely personal arena of micro-enterprises. In micro-enterprises, decisions are not periodic, high-level strategic deliberations made by committees; they are frequent, granular, and operational, directly linked to daily cash flow, immediate inventory needs, and week-to-week survival. Understanding the process—the minute-by-minute and day-by-day mechanisms—by which these biases infiltrate and influence these routine but essential choices is critical to explaining the endemic inefficiencies observed in this enormous segment of the global economy. This study aims to address this precise gap by arguing that to understand micro-enterprise failure, we must look beyond financial data and into the minds of micro-entrepreneurs.

We address this identified gap by designing and conducting a field experiment that renders the operational consequences of different decision-making logics not only observable but also richly interpretable. It is grounded in a core methodological premise—the "managerial mind" thesis: the belief that a manager's cognitive processes leave discernible, empirically analysable traces in an enterprise's operational history. These traces are evident in patterns of inventory orders, replenishment timing, and reactions to sales outcomes. Therefore, rather than relying solely on surveys or interviews that collect self-reported reasons for actions (which may be post-hoc rationalisations and cannot access subconscious biases), this research studies manifested behaviour through a controlled naturalistic comparison. It seeks to make materially visible what is cognitively invisible.

The central research question guiding this inquiry is: How does the operational manifestation of a human manager's decision-making process (which may be subject to cognitive biases) differ from a purely rule-based process, and what do these differences reveal about the fundamental sources of decision inefficiency in micro-enterprises?

To unpack this overarching question and ensure a structured investigation, this study formulates and systematically explores three interrelated research questions, each corresponding to a well-documented cognitive bias in the behavioural science literature:

RQ1 (Anchoring & adjustment): Do human managerial decisions exhibit a systematically different pattern of deviation from historical baselines compared to a rigid, rule-based anchor? Specifically, is human adjustment

more variable, less consistent, and potentially less responsive to clear environmental signals than a mechanical rule?

RQ2 (Situational responsiveness): How do the two decision systems differ in their responsiveness to the same predictable situational changes (e.g., weather fluctuations, scheduled campus events)? Do human managers integrate or filter these signals differently, and if so, what cognitive mechanisms underlie this filtering?

RQ3 (Learning and behavioural volatility): How rigidly is each system predisposed to altering its operational behaviour in response to success (e.g., sell-outs) or failure (e.g., significant overstock)? What does this imply for the causal mechanisms underlying the learning process? Additionally, is the human decision-making pathway characterised by stability rooted in Bayesian updating, or is it fraught with volatility marked by emotionally charged reactions to recent outcomes?

This research contributes to theory, methodology, and practice. Theoretically, it advances the micro-foundations of behavioural corporate finance and small business management by providing a rich, process-oriented account of how cognitive biases manifest in naturalistic business settings. It shifts the discourse from correlational analyses that examine relationships between bias proxies and firm-level outcomes to identifying the causal processes through which biases lead to specific types of inefficient actions. Methodologically, it demonstrates the utility and rigour of small-N, in-depth qualitative studies as powerful tools for causal inference and deep understanding in managerial contexts. This approach complements large-sample quantitative studies by providing the depth and explanatory power that breadth alone cannot achieve.

Practically, it seeks to generate actionable insights for entrepreneurs, business educators, and support organisations. By highlighting that a fundamental source of inefficiency may be cognitive and process-driven, it shifts the focus of intervention from simply providing more information or capital to designing decision processes, routines, and “hygiene” practices that mitigate inherent cognitive flaws and build more resilient business ventures.

The remainder of this paper is organised as follows. Section 2 synthesises the relevant literature, develops a conceptual framework integrating behavioural finance and operations management, and clearly identifies the theoretical gap addressed by this study. Section 3 details the research methodology, justifying the qualitative experimental design, explaining the case selection and matching process, outlining the data collection protocols, and describing the analytical strategy derived from process tracing and thematic comparison. Section 4 presents the main findings through narrative comparison of the two cases, analyses the most significant decision episodes that illuminate the divergence in their operational pathways, and crystallises these into dominant thematic patterns. Section 5 discusses the broader implications of the findings, explores their theoretical contributions, translates them into practical applications for entrepreneurs, acknowledges the study’s limitations, and suggests coherent directions for future research. Finally, Section 6 concludes with a summary of the main arguments and a reflection on the overarching message of the study regarding micro-enterprise decision-making.

Literature Review

The dominant agency theory (Jensen & Meckling, 1976) frames investment distortions as a product of conflict between owners and managers. However, in owner-managed micro-enterprises, this principal-agent conflict disappears as incentives are fully aligned. Despite this, high failure rates and operational inefficiencies persist—a paradox that agency theory cannot resolve (Baker & Ricciardi, 2014). This impasse necessitates an alternative model centred on the cognitive structure of the decision-maker, shifting the focus from incentive structures to the internal processes of judgment and choice.

The behavioural revolution, rooted in Simon's (1955) concept of bounded rationality and Kahneman and Tversky's (1979) heuristics and biases framework (including prospect theory), has challenged the axiom of perfect rationality. It identifies systematic cognitive biases as major causes of anomalous decision-making. A core insight from this literature is Kahneman's (2011) dual-system theory of thinking, which distinguishes between two modes of cognition: System 1, the fast, automatic, intuitive, and emotional mode; and System 2, the slow, deliberate, analytical, and rational mode. Most everyday decisions are made by System 1, which is prone to cognitive biases, while System 2 requires effortful activation to override intuitive errors.

For corporate operational and investment decisions, three biases are of particular relevance:

Overconfidence: Leads decision-makers to overestimate their knowledge and control, resulting in value-destroying mergers and over-investment (Malmendier & Tate, 2005; 2015).

Anchoring & insufficient adjustment: Causes decision-makers to rely excessively on an initial reference point (e.g., historical data), leading to flawed forecasts (Tversky & Kahneman, 1974).

Recency bias & the law of small numbers: Creates a tendency to overweight recent, salient events, and draw broad conclusions from small samples, leading to volatile and overreactive decision-making (Gilovich, Griffin, & Kahneman, 2002).

However, a major gap remains: This literature typically uses indirect proxies for bias (e.g., CEO media portrayal) in large-firm datasets, leaving the in-situ enactment of biases in micro-enterprises understudied.

Existing research on behavioural factors in Small and Medium Enterprises, SMEs (e.g., Benayad & Aasri, 2023; Hartoto, Setyawan, & Nurdin, 2024) often relies on self-reported qualitative data such as surveys, which are inherently limited by post-hoc rationalisation and the inability to capture subconscious biases. Meanwhile, the field of Behavioural Operations Management (BOM) has emerged, focusing on the intersection of psychology and operational management issues such as demand forecasting and inventory control (Bendoly, Donohue, & Schultz, 2006; Syntetos, Babai, & Gardner, 2016). However, the synthesis of BOM's process-oriented lens with the unique, high-pressure context of owner-managers who assume multiple roles remains underdeveloped. This creates a disconnect between macro-level correlations of biases and micro-level behavioural processes. While previous studies in small business management have analysed cognitive biases in SME investment decisions (Radicic & Pugh, 2017; Taura & Radicic, 2019), they have been based on cross-sectional surveys or archival data, leaving the dynamic, process-level mechanisms of bias enactment unexamined. This research addresses this gap by presenting granular, longitudinal evidence of how cognitive processes related to anchoring, overconfidence, and recency bias lead to divergent operational pathways and inventory inefficiencies in a real-world micro-enterprise setting.

A clear divide exists between outcome-focused evidence from large firms and process-based understanding in micro-enterprises. The missing link is a micro-level, process-tracing account of how biases are enacted in daily operations where agency issues are absent. This study's conceptual framework posits that the owner-manager's biased cognitive system acts as the central processor interacting with the operational context, producing decisions that lead to outcomes such as stock-outs or overstocks. Feedback from these outcomes is then interpreted through the same biased filter, creating a self-reinforcing cycle of inefficiency. To isolate this effect, the study employs a comparative experiment between a human-managed case and a rule-based control case. This design is intended to track the behavioural "footprints" of mental errors (Serman, 1989), attributing divergences in operational paths to the intervening variable of biased mental calculations.

Research Methodology

This research adopts a pragmatic philosophical stance that integrates realism and interpretivism. It rests on the realist assumption that cognitive biases are objective psychological mechanisms that produce real-world, observable consequences in operational data. Simultaneously, it embraces an interpretivist perspective, which holds that the meaning, logic, and rationality underlying managerial actions must be understood within their specific socio-material context: A number in an operational log is not merely a quantitative value, but the outcome of a situated judgment.

The selected design is a qualitative comparative experiment (Yin, 2018). It is important to clarify that this is not a statistical experiment in the positivist tradition seeking generalisable proof through large samples and null hypothesis testing. Rather, it is a theory-guided experiment aimed at causal explanation and mechanism tracing. The deliberate manipulation of the independent variable—the decision logic (human intuition vs. pre-set rules) applied to otherwise identical assets—creates the conditions for observing, describing, and deeply interpreting the resulting divergent processes (the dependent phenomena). The strength of this design lies in its ability to retain the complexity of the real world and answer “how” and “why” questions about process and causation, which are difficult to address through variable-centred quantitative methods alone. It is consistent with the abductive approach to studying empirical puzzles (divergent paths), where explanations are constructed by iteratively referencing existing theory (behavioural science) at various stages of analysis (Timmermans & Tavory, 2012).

The research was conducted within the operational ecosystem of “CampusRefresh” (a pseudonym), a small entrepreneurial venture operating beverage vending machines at a large university in Eastern China. To ensure a meaningful, controlled comparison and minimise confounding variables, two machines were selected using purposive matched sampling. The primary matching criteria were: same building location (main university library), similar customer profiles (students and staff), identical product assortments and pricing, and comparable historical sales volumes in the previous year.

Experiment Case (EC): The machine located in the library’s main lobby. This machine was assigned to the owner-operator, who was instructed to manage it “as he normally would, using his best judgment, experience, and all available data to maximise profitability”. He had full, unrestricted access to a digital dashboard showing sales history by product, day of the week, and machine. No algorithmic suggestions, decision rules, or mandates were imposed. This setup was designed to preserve the “natural state” of owner-manager decision-making, including both its potential for intuitive insight and its susceptibility to cognitive bias.

Control Case (CC): The machine located in the library’s quiet study hall. This machine was managed using a Simple Deterministic Rule Set, encoded in a weekly worksheet provided to the owner-operator.¹

The rules were explicit, transparent, and designed to be context-aware but entirely non-cognitive—devoid of judgment, intuition, or learning:

1. Base rule: Replenishment quantity for a given product on a given weekday = Sales quantity of that product on the same weekday the previous week.

2. Environmental rule (temperature): If the forecasted average temperature for the next day is more than three degrees Celsius higher than the temperature on the same day the previous week, increase the order quantity

¹ The same owner-manager operated the two machines according to the different rules, in order to minimize confounding variables (extraneous factors).

for all chilled beverage Stock Keeping Units (SKUs) by two units.

3. Event rule (exams): If the day is officially marked as an “Examination Day” on the university’s published academic calendar, add 5 units to all coffee-based drink SKUs.

The owner-operator performed the physical replenishment for both machines but was required to follow the CC worksheet exactly, treating it as an automated system instruction. This ensured that any differences in outcomes were due to decision logic rather than execution. The study period spanned eight consecutive weeks, which was deemed sufficient to observe patterns, responses to different conditions (routine academic weeks, major examination periods, seasonal weather changes), and the stability or volatility of each system’s behaviour.

Consistent with the study’s core objective of tracing revealed behaviour (and avoiding the pitfalls of self-report data), data collection was strictly focused on objective operational and contextual data.

First, core process data (the action trail) were collected through two primary channels. Daily inventory audit logs were maintained using a standardised protocol for manual, twice-daily inventory audits. Stock levels for every product slot in both machines were recorded at the beginning (before first sales) and end (after last sales) of each business day. This generated an accurate, timestamped record of inventory depletion, the fundamental trace of operational efficiency. Replenishment action registers were also kept, where every restocking action was logged with machine ID, date, exact timestamp, product SKU, and quantity added. For EC actions, brief, objective observational notes were made (through direct observation or immediate inquiry) of the data consulted just before a decision was made (e.g., “scrolled through phone dashboard for ~10 seconds, focusing on last week’s column”, “verbalised to himself: ‘yesterday sold really well here’”).

Second, contextual data (the operational environment) were collected to capture external factors that might influence demand. An environmental and event log was maintained daily, recording objective external conditions such as maximum/minimum temperature, precipitation, and academic calendar status (e.g., “Week 5, Monday: Mid-term exams begin”, “Week 7, Friday: Public Holiday, campus quiet”). Non-participant structured observations were conducted by one of the researchers for 30-minute intervals every two weeks at each machine location during peak traffic hours. Notes focused on objective factors such as adjacent foot traffic patterns, presence of competing temporary food stalls, maintenance issues, and any other observable events that could affect demand.

Third, artifact data (the decision instructions) were collected to document the decision-making processes. The CC rule sheets, which served as the material embodiment of the Control Case’s decision logic and a check on protocol adherence, were retained. A researcher reflexive journal was also kept to record methodological decisions, developing analytical hunches, potential personal biases, and ethical considerations throughout the research process, enhancing the confirmability and auditability of the study.

The analysis employed an abductive reasoning approach (Timmermans & Tavory, 2012), which involves iteratively moving between empirical data, emerging patterns, and the theoretical framework of behavioural decision science to construct the most plausible explanation.

The first step was to construct thick, temporal case narratives for each machine. Inventory logs, replenishment data, and contextual data were integrated into a comprehensive, day-by-day history of each machine’s operational life, including its regular rhythms, responses to shocks, and steady-state behaviour. This narrative construction required deep immersion in the data and emphasised cause-and-effect relationships. Within these rich narratives, specific critical decision episodes were identified for in-depth analysis. These were clusters of actions and outcomes surrounding significant events, such as replenishment cycles before and during

exam week, responses to the first day of an unexpected heatwave, and actions taken in the days following a major stock-out or significant overstock. These episodes served as natural “stress tests” for the two decision systems.

A comparison matrix was then developed to facilitate side-by-side comparison of matched episodes from EC and CC (e.g., their respective pre-exam replenishment decisions) at a fine-grained level of detail. For each episode, the analysis focused on six key dimensions: the trigger that initiated the decision, the objective signals that existed and the signals that were actually used, the explicit rule (for CC) or implied heuristic (for EC) that guided the decision, the quantitative order quantity taken, the immediate resulting sales and inventory state, and the interpreted behavioural signature or thematic category that the episode exemplified.

Through constant comparison of these episodes across the eight-week timeline, recurrent and systematic differences between the EC and CC pathways were grouped into global thematic categories. These themes were not pre-defined but emerged inductively from the data, describing the fundamental, contrasting operational behaviour archetypes that characterised each decision system. The process was iterative, with themes being refined, merged, or split as analysis progressed.

Finally, the identified themes were critically reviewed against the behavioural literature reviewed in Section 2. The purpose was to determine whether the patterns exhibited in the human-managed case (EC) were consistent with the predictions and descriptions of cognitive bias theory (e.g., anchoring, overconfidence, hot-hand fallacy). This step involved moving from description (“the human adjusted slightly from the anchor”) to explanation (“this reflects the anchoring and insufficient adjustment heuristic”), thereby constructing a coherent, evidence-based explanation for the systematic divergence between the two pathways.

To ensure rigour and reproducibility, this study uses established standards for qualitative research (Lincoln & Guba, 1985) to ensure credibility and soundness, addressing concerns about subjectivity in single-case experiments. Specifically, credibility (internal validity) is achieved through methodological triangulation (combining case study, process tracing, and comparative analysis) and data source triangulation (corroborating process logs, contextual logs, and artifact data). An active search for disconfirming evidence was conducted throughout the analysis. To ensure dependability (reliability), a detailed analytical audit trail was maintained, including all raw data logs, comparative analysis matrices, iterative coding notes, and reflexive journal entries, enabling scrutiny and verification of the research process and decisions. Furthermore, to ensure confirmability (objectivity), we used the researcher’s reflexive journal to bracket preconceptions and acknowledge the dual role of observer and rule system designer. The explicit use of the rule-based system as a baseline also provided an objective counterfactual against which to compare human judgment. Finally, for transferability (external validity), we provide “thick description” of the cases, context, participant, and decision rules. This level of detail allows readers familiar with micro-enterprises or operational settings to make informed judgments about the potential applicability or resonance of the findings to contexts beyond campus vending machines. Generalisation is analytical (to theory) rather than statistical (to populations). Building on our rich qualitative case analysis, future research may develop new theories or test the theories using large samples.

Data Analysis

The empirical analysis revealed that two dramatically different operational realities emerged from the same commercial environment. The human-managed Experiment Case (EC) and the rule-managed Control Case (CC) not only produced different summary efficiency scores at the end of eight weeks, but also enacted fundamentally

distinct operational pathways—patterns of behaviour, decision-making, and adaptation over time that reveal the underlying logics of their activity.

Theme 1 Anchored Adjustment vs. Mechanical Rigidity: Baseline Decision Patterns

The most fundamental and persistent difference emerged in their default operational states during routine, low-volatility periods, which set the stage for their divergent responses to change.

The Control Case (CC): Mechanical replication of historical baselines. CC's operational pathway was characterised by mechanical rigidity. Its decision logic followed a simple, non-negotiable one-step rule: $f(t) = \text{Sales}(t - 7)$. If it sold 15 cans of iced tea on Tuesday of Week 2, it unfailingly ordered 15 for Tuesday of Week 3. In normal times, its inventory graph was an accurate, one-week lagged mirror of the past sales curve. There was no random variance or "noise". Its inefficiencies were open and predictable: It systematically under-ordered during periods of growing demand and over-ordered during periods of declining demand, with the magnitude and direction of errors entirely dependent on past trends. For example, during Weeks 1-3, when sales of a sports drink showed a gentle upward trend, CC's orders were consistently 1-2 units below demand, resulting in minor but chronic stock-outs. This was not an error of judgment, but an error of design—the failure to include a rule for adjusting to trends.

The Experiment Case (EC): Subjective adjustment around historical anchors. The owner-operator's management of EC exhibited a more complex pattern of anchored adjustment. Historical sales data were the undisputed central reference point for his decisions, cited in almost every log entry. However, he almost never adhered precisely to this anchor. One typical Thursday entry read: "Last Thursday: 18 sold. Weather is similar, but there's a late afternoon seminar in the next hall mentioned on the department website". Here, the anchor (18) was explicit, and the adjustment (+2) was based on a specific, situational hypothesis ("the seminar might boost sales"). On another occasion, an entry read: "Last Friday sold 25. Campus just seems pretty quiet today, I don't know why". Here, the adjustment (-2) was prompted by an intangible, global feeling ("feels quiet") for which there was no identifiable objective source. This created an operational pathway that closely tracked CC's but constantly oscillated around it, with small variable amplitudes (-3 to +3 units). These adjustments were not always calibrated to clear, recorded signals; they represented the "insufficient" and often arbitrary adjustment away from an anchor described in the heuristics literature (Gilovich et al., 2002). While sometimes beneficial (e.g., the +2 adjustment for the seminar), they sometimes introduced detrimental noise—variance that did not improve accuracy. This pattern reflects a decision system that recognises the anchor but adjusts it using an internally constructed subjective model of the world that is applied inconsistently.

Theme 2 Situational Filtering vs. Rule-Driven Response: Reactions to Predictable Exogenous Shocks

A key test between the two systems, and the point of sharpest divergence, was a period of high stress created by a predictable exogenous shock: a major university examination week. This period served as a critical test not merely of baseline adjustment, but of how each decision system processes clear contextual signals.

The academic calendar clearly marked the Monday of Week 4 as the first day of mid-term exams. This objective fact triggered CC's "Exam Rule", which automatically added five units to all coffee-based drinks. The EC's manager also verbally acknowledged the exam timetable during observation. However, his actual coffee replenishment order for that Monday was only two units above baseline, rather than five. The observational note recorded his reasoning at the time of the decision: "Saw the exam schedule. Prior operational experience suggested that during exams, students are either in such a huge rush that they just grab a water or energy drink,

or they bring a big thermos of coffee from home. They're not lingering here having a latte". The outcome data were unambiguous: CC sold out of its primary coffee product by 3:00 PM, while EC finished the day with three units of the same product left over—precisely the type of under-stocking and lost sales opportunity that defines decision inefficiency.

This divergence exemplifies situational filtering in its purest form. CC responded mechanically but fully to the objective, programmed signal; it had no "beliefs" to interfere. In contrast, the EC's human manager layered the identical objective signal onto a dense veneer of personal belief, anecdotal experience, and a specific causal model. This subjective internal model led him to actively discount the strength and generality of the clear external signal, resulting in a substantial under-reaction. This is a classic behavioural signature of overconfidence—in this case, overconfidence in the superiority of his personal, experience-based model over a simple rule—and a form of the "inside view" described by Kahneman and Lovallo (1993), where specific, detailed scenarios override base rate information. The operational consequence was not a random error, but a measurable, theory-predicted instance of under-investment (stock-out) directly linked to a cognitive bias—not a lack of information, as he had access to the same exam calendar as the rule system.

Theme 3 Volatile Outcome-Sensitive Learning vs. Stable Ignorance: Responses to Unexpected Feedback

Perhaps the most striking divergence lays in how the two systems responded to feedback, particularly to unexpected, salient events. This revealed their diametrically opposed philosophies of "learning" and adaptation.

A critical illustrative episode is the unforecasted sharp heatwave in Week 5. On the first day of the heatwave (Tuesday), both machines sold out of their chilled sports drink inventories by evening—an unambiguous signal of unmet, weather-driven demand. CC's rule set contained no provisions for "heatwaves" or other unanticipated demand spikes. It simply implemented its base rule, ordering the same quantity as the previous Tuesday (a cool day). As a result, it severely under-ordered and sold out again by mid-afternoon. In contrast, reacting to the salient, vivid, and financially tangible outcome of Tuesday's complete sell-out, the EC owner-operator placed an order 40% higher than the historical anchor on Wednesday. His log entry read: "Extremely hot yesterday, sold out completely. Need to load up today—won't make that mistake again". However, this resulted in significant overstock on Wednesday, as the peak of the heatwave had passed and demand, while still high, was not at the extreme level of Tuesday.

Importantly, this process did not end with a single over-correction. Faced with Wednesday's overstock, the EC owner-operator's next order for that product, on Friday, swung back down to the historical anchor. The pattern revealed a predictable, emotionally charged cycle: Salient Negative Outcome (Stock-out) → Strong Corrective Reaction (Over-Order) → New Negative Outcome (Overstock) → Corrective Over-Reaction in the Opposite Direction (Under-Order). This is the hallmark of volatile, outcome-sensitive "learning". It is fuelled by recency bias (overweighting the most recent, memorable event) and the hot-hand fallacy (incorrectly assuming that a short-term trend will persist). It reflects a non-Bayesian, non-regressive updating process in which beliefs and actions are wildly adjusted based on tiny samples (the law of small numbers), ultimately leading to significant path instability.

In stark contrast, CC existed in a state of stable ignorance. Its operational pathway was completely unaffected by the outcomes of the heatwave; it remained predictably consistent, contextually blind, and stable (if often incorrect). Its errors were consistent and systematic, while EC's errors were erratic, emotionally charged, and followed a pattern of overreaction and reversal. This very volatility is a major source of operational risk and

inefficiency, making performance unpredictable and planning difficult. Our evidence also suggests a possible cause of high failure rates among small businesses and micro-enterprises.

Discussion and Conclusion

Synthesising the Divergent Pathways: A Tale of Two Logics

This qualitative investigation has revealed two archetypal operational logics for micro-enterprises, each with its own inherent strengths and vulnerabilities. The Rule-Based Pathway (CC) is characterised by transparency, predictability, and rigid consistency. Its failures are failures of omission—the lack of a rule for specific contingencies such as heatwaves or gradual demand trends. It is, in a sense, “blindly consistent”, and its inefficiencies are analytically predictable given knowledge of the rules and the environment.

In stark contrast, the Human Manager Pathway (EC) is defined by its potential for flexibility and context sensitivity, but also by dangerous inherent instability. Its inefficiencies are failures of commission: the active (but often subconscious) introduction of bias and noise into the judgment process at the critical stages of adjustment, situational filtering, and learning. While capable of brilliant, context-aware adjustments (e.g., the +2 units for the seminar), it is equally prone to arbitrary adjustments (“feels quiet”) and systematic, theory-predicted errors (under-reaction to exams, overreaction to recent sales).

The core finding of this study is not that the human manager made more or fewer errors than the simple rule-based system, but that his errors formed coherent, theoretically interpretable patterns that systematically deviated from the rule-based baseline in ways precisely predicted by behavioural science. The “anchored adjustment” pattern provides a clear behavioural footprint of the anchoring and insufficient adjustment heuristic in a real business setting. The “situational filtering” observed during exam week is a classic example of how overconfidence in personal narratives combined with the “inside view” can override valuable statistical or situational cues, leading to under-reaction. The “volatile learning” in response to the heatwave demonstrates how emotional reactivity, recency bias, and non-regressive prediction destabilise operations, creating a cycle of over- and under-shooting. Together, these patterns provide definitive and convincing evidence that cognitive biases are not merely abstract personality constructs or statistical correlates of inefficient performance: They are enactive and structuring processes that directly influence the operational rhythm, risk profile, and performance efficiency of micro-enterprises. The human pathway is not just less efficient—it is differently and predictably inefficient.

Theoretical Contributions

This study makes three substantive theoretical contributions to the intersecting fields of behavioural finance, entrepreneurship, and operations management.

First, it provides granular, process-based evidence for theoretical constructs that are typically measured using distal outcomes or self-reported surveys. It responds to longstanding calls for research to open the “black box” of managerial and entrepreneurial decision-making (Powell, Lovallo, & Fox, 2011). By systematically tracing the “how” of bias enactment, it strengthens the micro-foundations of behavioural theory, demonstrating that biases such as overconfidence are not just variables that correlate with bad decisions at the firm level, but the very cognitive mechanisms that produce recognisable, sequential patterns of flawed actions at the operational level. This fills an important gap between abstract psychological theory and everyday managerial practice.

Second, it highlights the interactive and systemic nature of biases in practice. Biases never function in isolation. In the observed pathway, the initial decision point was based on anchoring to last week’s sales.

Overconfidence in a personal model then filtered incoming situational information (the exam signal), determining the direction and magnitude of adjustment. Finally, recency bias and the hot-hand fallacy drove the volatile “learning” from outcomes. These biases worked together to create a self-reinforcing machine of inefficiency, where the output of one biased stage became the input to the next. This systemic view suggests that interventions targeting a single bias (e.g., only debiasing anchoring) may be less effective than interventions that address the decision process as a whole, breaking the cycle at multiple points. The study thus advances the theoretical discourse from identifying which biases are important to understand how biases operate in concert within dynamic operational flows.

Third, it extends the application of behavioural operations management to the understudied context of owner-managed micro-enterprises. Most existing BOM research focuses on large organisations with specialised operational teams, but this study shows that the same psychological principles apply with even greater force in micro-enterprises, where a single individual makes all operational decisions. This contextual extension enriches the scope of BOM and provides a foundation for future research in this important sector.

Practical Implications: From Decision Support to Decision Hygiene

For practitioners, educators, and organisations supporting micro-entrepreneurs, these findings yield important, immediately actionable implications. The fundamental, perhaps counter-intuitive, point is that incremental improvements in micro-enterprise performance are not simply about providing better data analysis tools, more financial capital, or better market research—although these are important. It is as much, and arguably even more, about fostering better decision hygiene on the part of the entrepreneur. This includes devising simple structures and routines to compensate for known cognitive weaknesses. Specifically, the following decision support practices may be adopted:

1. Implement pre-commitment devices and simple rules: Entrepreneurs should be encouraged to codify their responses to predictable, recurring events. Creating written “if-then” action rules for exam periods, holidays, seasonal changes, or known local events (similar to CC’s exam rule) serves as a pre-commitment device. It binds the future (and potentially biased) intuitive self to a rational plan made in a calm state, avoiding the subjective filtering and under-reaction observed in the experiment.

2. Adopt structured decision checklists: Before finalising important operational orders (such as weekly inventory purchases), using a simple, structured checklist can interrupt automatic, intuitive System 1 thinking and force engagement of executive System 2 functions (Kahneman, 2011). Questions such as “What baseline number should I be anchored on?” and “What is the single best evidence arguing against my planned order?” can help reduce anchoring, confirmation bias, and overconfidence.

3. Institute process-focused reviews: Regular business reviews should include a conscious focus on analysing the reasoning behind decisions, not just their financial results. During reviews, ask questions such as: “That stock-out last week—was it bad luck, or did we forget to check the event calendar?” or “That overstock—were we still reacting to the sell-out the week before?” This promotes metacognitive awareness (thinking about one’s own thinking) and helps disrupt the cycle of volatile biased learning by separating outcome evaluation from process evaluation.

4. Design hybrid human-algorithmic systems: The study suggests that a hybrid model, rather than a choice between pure intuition and inflexible automation, is likely optimal. The proposed approach is: use a set of simple, understandable rules (like CC’s base + event rules) for routine, predictable replenishment decisions, and reserve

human judgment and creativity for truly novel situations, exceptions, and the higher-level task of periodically reviewing and updating the rules themselves based on long-term performance. This blended approach combines the stability and consistency of rules with the adaptive potential of human intelligence, while strategically containing the biases to which the latter is prone.

Limitations and Avenues for Future Research

Like any focused empirical study, this research has limitations that must be acknowledged and that point to promising avenues for future research. The depth of the study was achieved at the cost of statistical breadth. The findings from this two-case experiment in the specific context of campus beverage vending, while rich and informative, cannot be statistically generalised to all micro-enterprises or sectors. The rule set for the Control Case was deliberately simplistic to ensure clarity and contrast; a more sophisticated algorithm (e.g., incorporating moving averages or simple exponential smoothing) would likely have outperformed the human more consistently across all metrics and may have changed the nature of the comparative story. Furthermore, the study captures the behaviour of a single entrepreneur; individual differences in cognitive reflection, expertise, or risk tolerance could significantly moderate the observed effects. A more experienced or formally trained operator might exhibit different behavioural patterns.

Future research should build on this methodological approach and these initial findings in the following directions:

Multiple paired comparisons: Replicate this design across diverse industry sectors (e.g., retail boutiques, small food services, craft production) with different owner-managers. This would explore the robustness and variance of the identified behavioural patterns (anchored adjustment, filtering, volatile learning) and begin to identify sectoral or individual moderators.

Testing intervention protocols: Use a similar experimental framework to rigorously test the effectiveness of the proposed practical interventions (e.g., decision checklists, simple rule sets) in real micro-enterprises. This would shift the focus from descriptive insights to prescriptive testing, measuring the impact of such “decision hygiene” tools on both decision process stability and bottom-line operational performance.

Exploring the role of expertise and “Enterprising Grit”: Design studies to determine if and how deep domain expertise mitigates or exacerbates certain biases. Does expertise make intuition more accurately calibrated, or does it produce more persuasive (and thus harder to override) internal models that amplify overconfidence? Similarly, one may explore how the passion and perseverance of “grit” relate to cognitive biases—whether it manifests as productive persistence or biased escalation of commitment.

Conclusion

This study has demonstrated that cognitive biases are not just abstract psychological concepts, but tangible forces that shape the daily operations and performance of micro-enterprises. Through a unique comparative qualitative experiment, we have traced the behavioural footprints of anchoring, overconfidence, and recency bias in real-time inventory decision-making, showing how they lead to systematic patterns of stock-outs and overstocks. The findings challenge the conventional wisdom that more data or more capital are the primary solution to micro-enterprise inefficiency. Instead, they suggest that the greatest gains may come from improving decision processes to compensate for the inherent limitations of human intuition. By fostering better decision hygiene and designing hybrid human-algorithmic systems, micro-entrepreneurs can turn their cognitive weaknesses into strengths and build more resilient, efficient ventures.

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