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Qualitative Study of Organizational and Behavioral Barriers to AI Adoption among Malaysian SMEs

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Abstract:Despite a generally favorable policy landscape and widely available AI tools, Malaysia's small and medium-sized enterprises (SMEs) persistently have low adoption of AI technology. This study aims to explore the frictions around this tension by interviewing 20 leaders in the manufacturing, technology, and professional services sectors. Findings reveal that the constraints are more cognitive and cultural rather than technological or financial, knowledge deficits, collectively termed "AI illiteracy", and organizational inertia far outweigh the resource constraints. The most effective adoption enablers were localized training initiatives and an "AI-first" leadership mindset, not large-scale infrastructure investments. Value creation was primarily operational efficiency, speed, and quality, while strategic innovation remained unrealized. Through incorporating a human capital factor, this study reported that workforce literacy is a more significant factor in AI adoption than capital investment. Policymakers should shift from infrastructure subsidies to capability grants, while SME leaders should treat employees' up skilling as a prerequisite, not an afterthought for AI procurement.

Keywords: *Artificial intelligence, Malaysian SMEs, Mindset, Knowledge management.*

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I. INTRODUCTION

Artificial intelligence (AI) is changing competitive landscapes of businesses across the economy, however the adoption rates among small and medium-sized enterprises (SMEs) remain significantly lower than those of large corporations [1, 2, 3] . In Malaysia, while initiatives such as the National AI Roadmap 2021–2025 and infrastructure investments exceeding RM3 billion, over 50% of SMEs struggle to adopt AI effectively [4]. The adoption gap persists despite the AI tools have become more accessible to users including ChatGPT and Google Gemini and industry automation platforms. The current research about AI adoption depends on technology-oriented models which use the Technology-Organization-Environment (TOE) model[5] and Technology Acceptance Model (TAM) [6] are overlooked in human elements which include knowledge and cultural aspects that influence adoption decisions in SME contexts [7]. To fill this gap, this study explores AI adoption among Malaysian SMEs to look at human and organizational barriers besides technology reasons. The research is guided by three research questions:

RQ 1 What barriers shape SME owners' and managers' AI adoption decision-making?

RQ 2 What strategies do SMEs employ to overcome these barriers?

RQ 3 What forms of value creation and competitive advantage do SMEs attribute to AI adoption?

II. LITERATURE REVIEW

A. *AI Adoption in SMEs: Current Landscape*

Malaysian SMEs account for over 97% of business establishments and contribute towards 38% of the economy and 66% to the labor force [8]. Only 15-25% have adopted AI beyond simple automation [7, 9]. SMEs generally start with conversational AI and generative tools which lead to the subsequent automation of workflow and predictive analytics [10, 11]. However, their adoption path differs from large corporations due to resource constraints such as limited capital and skills shortages [12].

B. *Theoretical Frameworks and Gaps*

The TOE framework includes technology, organization and surroundings as factors for adoption [5]. Meta-analyses support its explanatory power [13],but criticism suggests that it does not sufficiently address factors related to people—employees, which include attitudes, skills and learning processes, which are key for AI adoption since human-AI collaboration is particularly salient [7].TAM focuses on perceived usefulness and perceived ease of use as determinants of individual technology acceptance [6], but its applicability to organizational-level AI decisions is limited, particularly in SME contexts where owner-manager preferences dominate[14]. Emergent scholarship frames knowledge management capabilities, a firm's capacity to obtain, assimilate and exploit AI knowledge as the true "meta-enabler" of adoption [15, 16].However, detailed empirical evidence from non-Western and resource-constrained SME environments remains limited [2].

C. *Barriers, Enablers, and Outcomes*

Previous research has defined technological barriers (integration complexity, data quality), financial barriers (implementation costs, ROI uncertainty), organizational barriers (insufficient management support, resistance to change) and human barriers (AI illiteracy, fears of job displacement) as major barriers [1, 10]. The enablers included top management support, training, test new approaches, government and vendor support [17, 7]. AI implementation leads to better operational performance through shorter production cycles, fewer errors, and higher production capacity though evidence from SME contexts remains limited [11, 18, 19].

III. METHODOLOGY

A. *Research Design*

This study adopts a qualitative, interpretive research design to examine SME owners' and managers' experiences with AI adoption, focusing on their perceptions and sense-making activities [20]. The interpretive paradigm is appropriate because it allows researchers to study personal meaning systems and observe people in their natural environments as they develop [21]. The research employs inductive exploratory methods because Malaysian SMEs have not yet implemented AI, and there is no established theoretical framework to explain this situation [22].

B. *Participant Selection and Sample*

Participants were chosen from criterion-based sampling to capture the information-rich cases [23]. The inclusion criteria consisted of (1) owner-managers or senior decision-makers who had authority over technology adoption; (2) employed at SMEs based on SME Corporation Malaysia; (3) operating in Malaysia; and (4) having adopted or seriously considered AI adoption. These recruitment efforts were accomplished through professional networks and industry associations (Malaysian SME Association). The representative sample consisted of 20 participants representing manufacturing (n=8), technology services (n=6), and professional services (n=6), including Managing Directors (n=9), Founders (n=6), CEOs (n=3), and senior managers (n=2) across Selangor, Kuala Lumpur, Penang, and Johor. The AI adoption levels included non-adopters/explorers (n=7), entry-level adopters (n=9), and intermediate adopters (n=4). Sample size is consistent with the guideline of thematic saturation[24, 25]. See Table 1 for participant demographics.

ID	**Role**	**Industry**	**Company Size**	**AI Adoption Level**	**Location**
P1	Director	Manufacturing (Precision Engineering)	Medium	Early exploration	Penang
P2	CEO	Technology Services (Cybersecurity)	Small	Entry-level	Selangor
P3	Managing Director	Manufacturing (Construction)	Medium	Early exploration	Penang
P4	Deputy GM	Manufacturing (Automotive)	Medium	Entry-level	Selangor
P5	CEO	Technology Services (AI Software)	Small	Intermediate	Kuala Lumpur
P6	Managing Director	Professional Services (Cabinet Design)	Small	Early exploration	Selangor
P7	Creative Tech Director	Professional Services (Creative Technology)	Small	Entry-level	Kuala Lumpur
P8	Founder	Technology Services (Blockchain)	Medium	Intermediate	Kuala Lumpur
P9	Managing Director	Manufacturing (Bio-organic Products)	Small	Early exploration	Selangor
P10	Marketing Manager	Professional Services (Market Research)	Medium	Early exploration	Kuala Lumpur
P11	Founder	Manufacturing (Factory Equipment Supplier)	Medium	Entry-level	Penang
P12	CEO	Technology Services (Cybersecurity/Cloud)	Small	Entry-level	Selangor
P13	Founder	Professional Services (Creative Technology)	Small	Entry-level	Kuala Lumpur
P14	Founder/Consultant	Technology Services (AI Consulting)	Small	Intermediate	Kuala Lumpur
P15	Founder/CEO	Professional Services (Financial Education)	Small	Early exploration	Selangor
P16	Managing Director	Manufacturing (Engineering)	Small	Entry-level	Penang
P17	Founder	Manufacturing (Electronics)	Medium	Early exploration	Johor
P18	Creative Tech Director	Professional Services (Creative Technology)	Small	Intermediate	Kuala Lumpur
P19	Director	Technology Services (AI Solutions)	Small	Entry-level	Selangor
P20	Managing Director	Manufacturing (Food Processing)	Small	Entry-level	Johor

Note: AI adoption levels: *Early exploration* (exploring but not implementing), *Entry-level* (using generative AI, chatbots), *Intermediate* (workflow automation, analytics). Company sizes per SME Corporation Malaysia (2023): *Small* (RM300k–RM15m revenue or 5–75 employees), *Medium* (RM15m–RM50m revenue or 75–200 employees).

Table 1. Participant Demographics and Organizational Characteristics.

C. Data Collection

Semi-structured interviews (August-December) were conducted with protocol including three domains: barriers (RQ1), enablers (RQ2) and outcomes (RQ3). Interviews were either face-to-face (n=14) or video conferencing (n=6) and approximately 45-90 minutes (M=62, SD=12) of transcribed 280 pages. All sessions were audio recorded with informed consent and verbatim transcribed. Theoretical saturation was achieved with participant 15, and interviews 16-20 were conducted to confirm that no new themes emerged and to strengthen the robustness of the findings [25].

D. Data Analysis

Thematic analysis with reflexive coding was conducted using 24 six-phase approach in NVivo 14. The first round of coding produced 127 descriptive codes grouped into 22 sub-themes, which were summarized into six over arching themes consistent with the research questions. Analysis used deductive (TOE guided) and inductive (emergent pattern) coding [26]. The inter-coder reliability yielded Cohen's κ =0.78, meaning a substantial amount of agreement between the independent dual coding performed on 20% of the transcripts[27]. The credibility was established by prolonged engagement and member checking through (n=5 participants) validating findings and triangulation across data sources [21]. University ethical approval was obtained, all participants completed written informed consent with anonymity ensured through pseudonymous.

IV. RESULT

A. Overview of AI Adoption Landscape

The participants in this study demonstrated varied yet distinctly early-stage engagement with AI: non-adoption/exploration (n=7), entry-level adoption targeting the generative interfaces (n=9), and intermediate adoption through the structured workflow automation (n=4). They had no advanced adoption (bespoke ML models or autonomous systems). The most commonly used tools included ChatGPT (n=15), Google Gemini (n=7), DeepSeek (n=7), and Microsoft Copilot (n=4). Mean organizational AI adoption on a 1-10 scale was 3.8 (SD=1.6). And importantly, 11 participants compared individual use of AI with organizational adoption systematic integration, revealing the divergence of awareness to institutionalization. Adoption motives were examined focused mainly on efficiency and productivity (n=13), competitive pressure (n=9), and cost reduction (n=7), but innovation was addressed by three respondents indicating a defensive mindset. Efficiency motivations emphasized time savings: "Instead of taking one week to design proposals, now we can do it in two hours using AI-generated images" (P7). Competitive pressure reflected client expectations and peer benchmarking: "When I see competitors adopting AI, I worry we'll be left behind" (P3).

B. RQ1: Barriers to AI Adoption

Five interconnected barrier clusters emerged across all 20 participants. Most pervasively, knowledge and awareness deficits (n=20), manifesting as AI illiteracy at four levels: conceptual confusion (inability to distinguish AI from automation), use case blindness ("I know AI can help, but I don't know where to apply it in my business"—P6), prompting skill deficits ("The quality of AI's answer depends 100% on how you ask the question"—P13), and an inability to articulate a strategic AI roadmap. Six participants experienced pilot-to-production failures traceable directly to these knowledge gaps. Cultural resistance and organizational inertia (n=13) they reported fear of job displacement persisting even after explicit no-layoff assurances, while nine described a risk-averse "wait and see" mentality rooted in past technology investment failures. A generational perspective: younger employees viewed AI as a skill-building opportunity, while older ones saw it as a threat. Financial and technical barriers were significant but frequently perception driven. Cost concerns (n=15) often reflect the high total cost "The software license is only 30% of the total cost," one cautioned. "The other 70% is on getting human capital trained, data cleaned, processes transformed" (P14). Yet some were unaware of the low-cost options such as micro-SaaS and pay-per-use models, indicating knowledge cost conflation. The uncertainty ROI: "How do I know if AI will save money? Nobody can guarantee" (P6). Technical challenges (n=9) centered on fragmented, particular issues were data silos, incomplete records, unstandardized formats, and a lack of data governance. "70% of our workflows are still manual. People fill out paper forms, then someone types them into a computer. You can't apply AI when everything is on paper" (P9). Overlaying all of these, ecosystem and policy gaps (n=11) further constrained adoption. The government grants existed in principle but were inaccessible due to bureaucratic processes and long approval timelines, while nine participants reported trust eroding vendor experiences of over promising and under delivering, prompting calls for formal vendor certification.

Barrier Theme	Sub-Barriers	Frequency (n)	%
Knowledge & Awareness Deficits	AI illiteracy, use case blindness, prompting skill gaps, strategic vision gap, pilot-to-production failure	20	100%

Barrier Theme	Sub-Barriers	Frequency (n)	%
Cultural Resistance & Inertia	Fear of job displacement, “wait and see” mentality, risk aversion, AI fatigue, generational divide	13	65%
Cost Perceptions	High implementation costs, ROI uncertainty, hidden costs, subscription fatigue	15	75%
Technical & Integration Challenges	Poor data quality, data silos, legacy system incompatibility, manual processes, lack of data governance	9	45%
Ecosystem & Policy Gaps	Policy-implementation disconnect, bureaucratic grant processes, vendor over-promising, trust deficit, lack of vendor regulation	11	55%

Table 2. Frequency of AI Adoption Barriers (n=20).

C. RQ2: Strategies and Enablers

All 13 adopters identified learning and capability building as the critical enabler, operationalized through formal training workshops, vendor-led knowledge transfer, online self-learning like YouTube, Linked In Learning, and peer learning communities. Thirteen participants employed of "start small, learn fast" strategy piloting AI in low-risk, high-visibility tasks such as ChatGPT-assisted proposal writing and automated data entry before scaling. Five participants highlighted the importance of management-level training: “It’s not enough to train staff. If the boss doesn’t understand AI, he won’t allocate budget or change processes. Top-down knowledge is essential” (P14). Universally, top management support activated the adoption process, manifesting as budget allocation, strategic prioritization, personal championing, and deliberate protection from short-term ROI pressure (“Owner said, I’m giving you one year to experiment. Don’t worry about immediate profits, just learn”—P7). Five participants institutionalized an "AI-first mindset" at the leadership level, "Can AI do this?" before approving any new hire or software request, normalizing AI as a default organizational consideration. Change management and external ecosystem strategies addressed resistance and cost constraints respectively. Seven participants who navigated employee resistance framed AI as “assistant, not replacement.” “We told staff: AI handles boring repetitive work so you can focus on creative, strategic tasks. You won’t lose your job; your job will become more interesting” (P1). On the external front, five participants leveraged strategic vendor partnerships. “We partnered with a local AI company that understood SME constraints. They didn’t just sell software, they provided training, customization, and ongoing support. They became our AI consultants” (P2). Eight participants applied for government grants, however six participants criticized bureaucratic complexity from applying despite qualifying. Adaptive cost strategies used cost minimizing techniques such as freemium tools and micro-SaaS, implementation beginning with single-purpose applications before expanding. Seven participants adopted a modular, phased approach to manage complexity: “We didn’t implement AI across the whole company at once. We started with one department—marketing. Once it worked, we expanded to sales, then operations” (P5). See Table 3 for enabler summary.

Enabler Theme	Specific Strategies	Frequency (n)	%
Learning Pathways & Capability Building	Formal external training, vendor-led knowledge transfer, online self-learning, peer learning communities, cascade training model, “start small, learn fast” pilots	13	100%
Leadership Vision & Support	Budget allocation, strategic prioritization, personal championing, AI-first mindset, protection from short-term ROI pressure	13	100%
Change Management & Communication	Framing AI as “assistant not replacement”, transparent communication, employee involvement in tool selection, celebrating early wins, hands-on support, town halls with no-layoff commitments	7	54%

Enabler Theme	Specific Strategies	Frequency (n)	%
Vendor & Ecosystem Support	Strategic vendor partnerships, free trials/freemium tiers, industry-specific templates, flexible pricing, knowledge transfer	5	38%
Government Support	Grants/subsidies (50% matching funds), training programs	8	62%
Adaptive Strategies	Using free/freemium tools, micro-SaaS adoption, phased/modular implementation, API integration, cost-benefit analysis	7	54%

Table 3. Enablers and Strategies for AI Adoption (n=13 adopters).

D. RQ3: Value Creation and Competitive Advantage

Operational efficiency and productivity gains were mentioned most often (n=12). Time savings from jobs included proposal preparation reduced from one week to two hours instead (P7), AI chatbots resolving 60% of routine customer inquiries response (P5), and data entry automation reduced 70% of the time (P2). Seven participants reported quality improvements, more polished professional content, near-zero data entry error rates compared to a previous 5% baseline, and consistent customer service delivery. Critically, four participants noted that output quality was inseparable from prompting competence: “Garbage in, garbage out” (P13), reinforcing the centrality of AI literacy as both a barrier and an ongoing performance variable. Competitive positioning gains followed from these efficiency improvements mentioned by nine participants, tender submission accelerated by 2–3 days, customer response time dropped from 24 hours to one hour, and one firm attributed a rise in tender success rates from 30% to 45% partly to faster, higher-quality submissions (P7). Cost competitiveness and strategic outcomes were meaningful but more constrained. Six adopters deferred hiring through automation, RM120,000 per year in avoided salary costs in one case (P2), characterizing this as “maintaining headcount while growing revenue” rather than displacement, with three firms reallocating staff from low-value execution to high-value strategic work. Five participants reported a shift to data-driven decision-making through AI analytics, reducing reliance on owner-manager intuition in product and inventory decisions. Four identified sustainability co-benefits, including 15% material waste reduction (P1). However, strategic innovation outcomes remained limited across the sample, and three participants acknowledged long-term moral tensions about employment: “Eventually we’ll need fewer people. That’s good for profits but bad for society” (P12). The overall pattern suggests an early-stage, efficiency-defensive rather than transformative adoption posture, with 9 AI functioning as competitive necessity rather than differentiation source. See table 4 for summary outcomes and value creation.

Outcome Category	Specific Outcomes	Frequency (n)	%	Representative Metrics/Examples
Operational Efficiency	Time savings in proposals, customer response, data entry, reporting	12	92%	Proposal time: 1 week $\rightarrow$ 2 hours; Data entry time $\downarrow$ 70%
Quality Improvements	More polished content, error reduction, consistency in service	7	54%	Invoice error rate: 5% $\rightarrow$ near 0%
Competitive Positioning	Faster proposal submission, higher win rates, better responsiveness	9	69%	Tender success rate: 30% $\rightarrow$ 45%; Response time: 24h $\rightarrow$ 1h
Cost Competitiveness	Deferred hiring, resource optimization, salary savings	6	46%	Deferred 2 accountants = RM120k/year savings
Data-Driven Decision Making	Customer trend identification, predictive analytics, inventory optimization	5	38%	Product decisions: gut feeling $\rightarrow$ data-based

Outcome Category	Specific Outcomes	Frequency (n)	%	Representative Metrics / Examples
Sustainability Benefits	Waste reduction, energy optimization, extended equipment life	4	31%	Material waste ↓ 15%; Reduced overtime
Employee Empowerment	Skill development, marketability, better work-life balance	3	23%	Staff free from weekend overtime

Table 4. AI Adoption Outcomes and Value Creation (n=13 adopters).

V. DISCUSSION

This study's central finding challenges technology-centric adoption frameworks: knowledge deficits (100% of participants) and perceived lack of awareness constitute a more formidable barrier than financial constraints (75%) or technical complexity (45%). Unlike prior research emphasizing cost [28] , infrastructure [29] , and technical complexity, this is probably a perception, our study reveal that perceived rather than objective barriers drove non-adoption. Participants reporting prohibitive costs were often unaware of freemium alternatives, the complexity had not encountered user-friendly tools. This broadens the AI literacy literature to establish limitations at four levels of the organization: conceptual, strategic, operational, and implementation, indicating that generic awareness campaigns are insufficient [10].

Cultural resistance, commonly framed as technophobia, emerged as rational response to communicative ambiguity. When leaders failed to articulate AI's augmentation role or provide credible job security commitments, employees rationally interpreted adoption as downsizing precursor, consistent with media narratives. This reposition resistance from individual attitudinal issue[6, 30] to organizational trust deficit requiring transparent change management. Cost perceptions functioned as socially acceptable proxies for risk aversion [31], suggesting that cost education would prove more effective than subsidies alone.

Organizationally, adopters progressed through learning, not sourcing. The true adoption machinery was training, experimentation, and knowledge sharing, similar to absorptive capacity [15] and organizational learning [32]. The "AI-first mindset" embodies a cognitive repositioning aligning with dynamic capabilities [33] by integrating AI consideration into organizational routines [34]. Yet institutional decoupling [35], a set of well-designed policies frustrated by bureaucratic implementation, propelled SMEs into internal capability building, consistent with institutional voids in emerging markets [36]. Value creation remained efficiency-focused (92%), with competitive advantages eroding rapidly, positioning AI as competitive necessity rather than differentiation source. Sustainable advantage depends on complementary capabilities such as prompting skills, experimentation speed, and AI-first culture are difficult to imitate [37].

VI. PRACTICAL IMPLICATIONS

The implications for SME owners and managers, who are likely to allocate at least 50% of their AI budget to training and developing capabilities. For SME owners and management, capability before procurement. As the knowledge gap was the biggest barrier to adoption (100% of participants), SMEs should allocate at least 50% of their AI budgets to training, experimentation, and internal knowledge sharing rather than tool acquisition.

For policymakers, the evidence demands a reorientation from infrastructure-heavy subsidies (estimated at 80% of AI funding) toward capability-building grants, streamline six-month approval timelines, and establishing vendor certification modeled on frameworks like Singapore's CyberSafe program would address trust deficits. For educators, role-specific, hands-on micro-credentials (3–5 day programs) and peer learning communities should address both AI skills and AI anxiety simultaneously. For vendors, an "educate before sell" model with transparent pricing, provide realistic ROI timelines, flexible pricing such as freemium or pay-per-use , and robust post implementation support would rebuild the trust that over-promising has eroded.

VII. LIMITATIONS AND FUTURE RESEARCH

Purposive sample of 20 participants informed the rich contextual knowledge but did limit the statistical generalizability of the study [38]. The participants are geographically localized in urban Malaysia such as Selangor, Kuala Lumpur, Penang, and Johor, as well as being non-representative of rural SMEs with limited access to re-11sources like connectivity and talent availability. Data collection is a cross-sectional (single-point-in-time) design that yields participants' present perceptions without longitudinal trends [39]. Interview self-reporting also heightens the risk of social desirability bias, when individuals overestimate how extensive the application is to appear original or underestimate failures to save face [40]. Future research should make use of stratified sampling by geography and adoption stage and use longitudinal case studies (2–3 years) to capture adoption dynamics and triangulation with objective performance data and employee perspectives.

VIII. CONCLUSION

This study reframes AI adoption in Malaysian SMEs as a human capital challenge and not simply a problem of technology or resources. Through thematic analysis of 20 in-depth interviews, we demonstrate that adoption barriers are fundamentally human organizational rather than technological and financial. This AI literacy gap encompasses conceptual, strategic, operational, and prompting competencies, creates self-reinforcing non-adoption cycles where firms cannot recognize opportunities regardless of resource availability. Cultural resistance, though pervasive, is more accurately conceived of as a rational organizational response to communicative uncertainty rather than technophobia. Successful adopters moved up the funnel through learning pathways, leadership championing and an embedded, AI-first mindset, achieving tangible improvements in efficiency, while strategic innovation stayed underrealized.

Theoretically offers a response to the absence of a long-standing adoption literature by placing the human capital and cultural preparedness of users at coequal importance as well as the technological, organizational and environmental determinants. These conclusions bear implications that policymakers must prioritize capability development over technology subsidies, and SME leaders need to ensure that knowledge about AI in the workforce is seen as the necessary precondition of any technology investment.

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