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Artificial Intelligence in Australian Fashion Businesses: An Exploratory Study of Adoption and Challenges

Amrutha Baburaj, Saniyat Islam * and Caroline Swee Lin Tan

School of Fashion and Textiles, RMIT University, Melbourne 3056, Australia;
amrutha.baburaj@rmit.edu.au (A.B.); caroline.tan@rmit.edu.au (C.S.L.T.)

* Correspondence: saniyat.islam@rmit.edu.au

Abstract

Artificial intelligence (AI) is reshaping the global fashion industry, yet its adoption within the Australian market (a geographically isolated, SME-dominated sector) remains under-researched. This study explores the current state of AI implementation, the principal barriers, and the perceived opportunities in Australian fashion businesses, with particular attention to sustainability. Using a qualitative, exploratory design, we conducted semi-structured interviews with nine professionals spanning fashion-technology start-ups, sustainable manufacturing, textile recycling, ethical certification, and global retail planning, and analyzed them thematically through the Technology–Organization–Environment (TOE) framework. The findings indicate that AI adoption is nascent and fragmented, typically entering firms through vendor-embedded features rather than deliberate strategy. Contrary to international studies that foreground cost and data infrastructure as primary barriers, participants in this sample identified a risk-averse organizational culture and limited perceived need as the dominant constraints. Sustainability emerged as the most significant yet largely unrealized opportunity, spanning reduced overproduction, fewer size-related returns, and improved textile recycling. These exploratory insights offer a context-specific reading of the TOE framework, suggesting that organizational culture may weigh more heavily than technological capability in isolated, SME-dominated markets, and that cultural change, supported by tiered education and industry-specific value propositions, is needed to realize AI's sustainability potential.

Keywords: Artificial Intelligence (AI); fashion industry; Technology–Organization–Environment (TOE) framework; digital transformation; organizational culture; sustainable innovation

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1. Introduction

The fashion industry, long criticized for its environmental footprint and inefficient supply chains, is at a critical juncture [1,2]. Characterized by overproduction, high return rates, and complex global logistics, the sector is responsible for a significant portion of global carbon emissions and textile waste [3]. In response, a paradigm shift towards sustainability and circularity is gaining momentum, pressuring brands to rethink every aspect of the value chain, from material sourcing to end-of-life [4]. This shift is increasingly underpinned by a tightening global and domestic regulatory landscape. Legislative pressures such as the European Union's Strategy for Sustainable and Circular Textiles and the Ecodesign for Sustainable Products Regulation (ESPR) are compelling businesses to move

beyond voluntary “green” initiatives toward mandatory compliance and transparent reporting [4]. In the Australian context, policy discussions surrounding the “Seamless” product stewardship scheme and the Modern Slavery Act 2018 are further intensifying the need for accountability [5,6]. These regulatory concerns, centered on transparency and waste reduction, act as primary drivers for rethinking material sources and establishing robust end-of-life practices to ensure long-term market access and ethical compliance [7].

Concurrently, the rapid advancement of Artificial Intelligence (AI) has emerged as a powerful transformative force, offering a suite of technologies, from machine learning (ML) and computer vision (CV) to generative AI, capable of addressing these endemic challenges [8,9].

However, the narrative of AI as a universal panacea warrants critical interrogation. While AI promises unprecedented efficiency, its adoption carries significant socio-technical risks that remain insufficiently explored within the fashion industry’s discourse. These include potential job displacement within creative and administrative roles, the reinforcement of systemic biases through opaque algorithmic decision-making, and profound concerns regarding data privacy and intellectual property [10]. Furthermore, the environmental cost of the computational power required to train large-scale AI models creates a paradoxical tension with the industry’s sustainability goals [11].

Despite these complexities, the Australian fashion industry presents a unique context. As detailed by the Australian Fashion Council [12], the industry is a vital \$27 billion sector dominated by Small to Medium Enterprises (SMEs). It operates with geographic isolation, a unique seasonal calendar, and a distinct business culture [13,14]. Much of the existing literature focuses on cost or data complexities as primary barriers [15], often assuming the benefits of AI without critically assessing the trade-offs. This study seeks to fill that gap by providing empirical, qualitative data from professionals working within the industry, explicitly weighing the perceived opportunities against these underlying risks.

The aim of this study is to examine how AI is being adopted in Australian fashion businesses and to identify the factors that enable or constrain that adoption, with particular attention to sustainability. To this end, the study addresses the following research questions:

1. How is AI currently being implemented within Australian fashion businesses?
2. What are the primary challenges and barriers hindering wider AI adoption?
3. What are the most significant opportunities for AI to enhance business performance?

This paper examines the current state of AI adoption within the fashion industry using the TOE framework to explore how technological, organizational, and environmental contexts influence the adoption process. Rather than presupposing the nature of the barriers, the analysis treats their relative weight as an empirical question, building on prior work that identifies organizational culture and readiness, not only cost or infrastructure, as decisive in SME technology adoption [8,15].

2. Literature Review and Theoretical Framework

2.1. Artificial Intelligence as a Strategic Enabler in Fashion

Artificial intelligence (AI) has evolved into a general-purpose technology transforming how organizations operate, innovate, and create value. It encompasses multiple sub-fields, including machine learning (ML), deep learning, natural language processing (NLP), and computer vision (CV), which enable machines to learn from data, identify patterns, and make autonomous decisions [8]. Existing literature on AI adoption is helpfully categorised through the Technology–Organization–Environment (TOE) framework,

which distinguishes between the characteristics of the innovation itself, the internal readiness of the firm, and the external market pressures [16].

In the fashion industry, AI integrates creativity, production, retail, and sustainability by supporting data-driven design, accelerating product development, and enabling predictive insights that enhance efficiency and reduce waste [1,2]. Generative design systems such as Generative Adversarial Networks (GANs) and diffusion models allow designers to experiment with silhouettes, colours, and textures derived from extensive datasets, shortening design cycles and reducing sampling costs [17,18]. However, AI's 'black box' nature poses a significant barrier for designers who value creative agency [19], particularly for Australian boutique labels where algorithmic opacity threatens the artisanal authenticity central to their value proposition [10]. The environmental cost of training large-scale models is also frequently overlooked, suggesting the technological pillar must be balanced against its sustainability footprint [20].

AI also raises philosophical questions regarding authorship and artistic autonomy. Marku [21] argues that algorithmic co-creation may dilute designer identity, while Särämäkari and Vänskä [22] conceptualise designers as hybrid entities combining human intuition with computational intelligence. This tension reflects the organisational dimension of the TOE framework, where internal culture and creative identity determine a firm's readiness to integrate machine-generated output [10].

In retail, virtual fitting rooms, style recommendation systems, and conversational shopping assistants are redefining customer interaction through computer vision and predictive analytics [23,24]. Platforms such as ASOS and Zara employ AI to predict purchasing patterns and optimise merchandising [25], while agentic AI automates omnichannel processes and delivers personalised shopping experiences [26]. However, deployment is mediated by the regulatory environment: data privacy and consumer consent are governed by frameworks such as the GDPR and Australia's Privacy Act [27], demonstrating that AI adoption is as much a response to environmental pressures as a technological choice. For Australian firms, geographic isolation and high domestic operational costs make predictive accuracy a survival requirement rather than a competitive luxury [28,29].

AI's contribution to sustainability is also significant. Predictive analytics reduce overproduction and unsold inventory, while AI-enabled defect detection enhances quality control [3,30]. Blockchain and IoT integrations enable supply chain traceability and ethical compliance [31]. Legislative shifts such as the EU's Ecodesign for Sustainable Products Regulation (ESPR) and Australia's stewardship schemes are increasingly compelling firms to adopt AI for mandatory traceability rather than purely competitive reasons [32].

Global market projections underscore AI's strategic importance, with the AI in fashion segment forecast to grow at a compound annual growth rate of 38.5% from 2021 to 2028 [33]. Yet adoption remains uneven: large multinationals lead innovation while SMEs struggle with financial and infrastructural constraints [34]. Organisational readiness, cultural attitudes, technical capability, and cost pressures, rather than technology alone, are the decisive factors shaping this transition. Table 1 consolidates these insights across regions.

Table 1. Summary of International Studies on AI Adoption.

Study Type	Region	Key Findings
Quantitative empirical study (surveys & modelling)	China	AI adoption is driven by organizational climate and employee readiness; behavioral and cultural factors shape implementation [35].
Empirical study (global manufacturing firms)	Multi-region	Identifies major barriers including high implementation cost, lack of technical capability, insufficient digital infrastructure, and resistance to organizational change.

		Emphasizing the role of environmental pressures and regulatory demands [36].
Mixed-methods empirical study	Europe	Shows that creative industries face unique cultural and ethical concerns, including fear of losing creative authorship, low digital literacy, and hesitation around automation [37]. Notes that SME resource limitations slow adoption.
Survey study	USA	Designers hesitate to adopt AI due to skill gaps, concerns about originality, and limited training access [38].
Empirical study	India	SMEs identify high cost, lack of data infrastructure, and workforce capability gaps as primary adoption barriers; benefits emerge once implemented [39].

Across these studies, cost, infrastructure, and skills recur as the dominant barriers in survey-based and manufacturing contexts (China, India, USA), whereas the European creative-industry evidence foregrounds cultural and authorship concerns. None of these studies examine a geographically isolated, SME-dominated market in which cultural disposition might outweigh cost and infrastructure, which is the gap this study addresses.

2.2. The Australian Fashion Industry

The Australian fashion industry contributes more than AUD 27 billion annually to the national economy and employs over 220,000 people across design, manufacturing, retail, and creative services [13]. The sector encompasses established global labels, heritage brands, independent designers, Indigenous fashion collectives, and rapidly growing SMEs [40].

Within the TOE framework, Australia's geographic isolation and distinct seasonal calendar have traditionally served as structural barriers to global market integration, though recent literature suggests these are increasingly mitigated by AI-driven logistics and digital visibility [41]. Legislative pressures such as the 'Seamless' clothing product stewardship scheme are compelling brands to adopt AI-enabled traceability to meet mandatory sustainability benchmarks [4,32]. In the Indigenous fashion space, ensuring that data-driven tools do not compromise cultural intellectual property presents a critical organizational challenge, positioning AI adoption as a socio-cultural process where ethics must govern technological use [42].

Despite its strengths, the industry faces structural constraints. SMEs struggle with scalability, high production costs, and fragmented supply networks [14], with adoption further hindered by risk-averse culture and insufficient technological capability [43,44]. Within the TOE framework, environmental pressures including regulatory expectations and sustainability mandates act as key adoption drivers, while resource constraints and limited digital skills serve as significant barriers to diffusion [44,45].

2.3. Theoretical Frameworks for AI Adoption

Understanding the adoption of AI within the Australian fashion industry requires both structural and behavioural perspectives. This study integrates the Technology–Organisation–Environment (TOE) framework [16], which offers a comprehensive lens to analyse the multidimensional drivers and barriers of AI adoption across fashion enterprises.

Alternative models were considered but found insufficient for this study's purposes. The Technology Acceptance Model (TAM) explains adoption through two individual, attitudinal constructs (perceived usefulness and perceived ease of use) and therefore omits firm-level resources, leadership, and external regulatory pressure, which dictate corporate technology decisions [46]. The Unified Theory of Acceptance and Use of Technology

(UTAUT) adds facilitating conditions and social influence but remains an individual-acceptance model validated largely on end-users rather than organisational decision units and still lacks an explicit environmental or regulatory dimension [47]. Rogers' Diffusion of Innovations (DOI) similarly under-weights the external environment [44].

Because AI adoption in Australian fashion is shaped decisively by compliance pressures (the Seamless stewardship scheme, the Modern Slavery Act 2018, and evolving privacy law), the TOE framework is retained: it models the firm as the adopting unit and incorporates the environmental context that the individual-level models cannot. By applying TOE, this research moves beyond descriptive accounts of what AI can do, to a critical interrogation of how internal organisational readiness and external market pressures intersect to shape adoption pathways.

The Technology–Organization–Environment (TOE) Framework

The TOE framework explains technology adoption as a function of three contextual dimensions: technological, organizational, and environmental. The technological context considers the relative advantage, compatibility, and complexity of innovations [48]. In fashion, this involves assessing whether AI tools such as generative design platforms, predictive analytics, and intelligent inventory systems align with existing processes and enhance creative, operational, or sustainability performance [49]. The organizational context focuses on internal capabilities, including firm size, leadership commitment, digital literacy, and resource availability. While large fashion enterprises can allocate infrastructure and capital toward advanced AI systems, smaller firms often depend on agile practices, collaborative decision-making, and leadership vision to drive digital transformation [50]. The environmental context encompasses external pressures such as market competition, regulatory frameworks, consumer expectations, and sustainability imperatives [51]. In Australia, the growing emphasis on ethical production, transparency, and AI governance frameworks has intensified both the opportunities and compliance requirements for fashion businesses [52].

The strength of the TOE framework lies in its ability to assess the interplay between technological capability, organizational readiness, and environmental dynamics. It is particularly relevant to the Australian fashion ecosystem, where diverse business models and resource disparities coexist within an environment of rapid digital change. Figure 1 illustrates the interrelationship between these three dimensions, highlighting how technological, organizational, and environmental factors collectively influence decision-making in AI adoption within fashion businesses.

The three dimensions, Technological Context (characteristics of the innovation itself, including relative advantage, compatibility, and complexity), Organizational Context (internal firm-level factors such as size, leadership, digital literacy, and resource availability), and Environmental Context (external pressures including market competition, regulation, and sustainability mandates) are represented as overlapping domains. The bidirectional arrows indicate that these dimensions do not operate in isolation: technological capability shapes and is shaped by organizational readiness, while both are continuously influenced by the external environment. AI adoption outcomes emerge from the intersection of all three contexts.

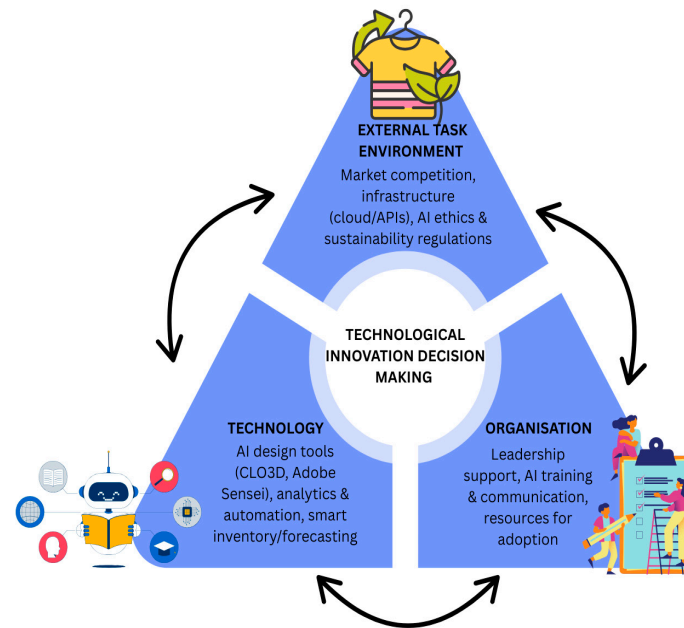


Figure 1. TOE Framework adapted from Baker [16].

Applied to the Australian fashion sector, the TOE framework provides a holistic understanding of how digital innovation unfolds across varying scales of enterprise. Large retailers implement advanced analytics and automation while SMEs rely on accessible third-party AI tools. The fashion sector’s creativity-driven culture can both encourage and inhibit adoption depending on managerial openness and workforce digital literacy, while shifting consumer demand for personalization, sustainability, and traceability further drives AI adoption across the value chain [52,53]. Taken together, the three literature strands map directly onto the three research questions: Section 2.1’s review of AI capabilities informs RQ1 (implementation); Section 2.2’s analysis of the Australian industry context underpins RQ2 (challenges and barriers); and Section 2.3’s framework justification establishes the analytical scaffold for RQ3 (opportunities), with the TOE framework serving as both the deductive basis for the interview protocol and the organizing principle for thematic analysis (Section 3.4).

3. Methodology

3.1. Study Context

This study is situated within the Australian fashion industry, selected as the empirical setting for several reasons that align with the research objectives. Approximately 85% of Australian fashion businesses are classified as SMEs operating with annual revenues under AUD 10 million [12], making the sector representative of the resource-constrained organizational profile at the center of this inquiry.

Objective data establishes a measurable baseline for AI adoption dynamics in this context. Fewer than one in three small Australian businesses had implemented any form of digital automation as of 2023, compared with over 60% of large enterprises [54]. Australia’s Productivity Commission has identified slower digital technology diffusion among smaller firms as a persistent structural challenge, with SMEs disproportionately affected by the lag behind the global productivity frontier [55]. Research from the Reserve Bank of Australia further confirms that larger firms adopt emerging digital technologies including cloud computing and AI at substantially higher rates, with scale advantages, liquidity constraints, and fixed adoption costs identified as key drivers of this divide [45].

Consumer demand remains robust, with Australians among the highest per capita apparel consumers globally, purchasing an average of 27 kg of clothing annually [56], a pattern that intensifies sustainability pressures on the industry. Brands such as Zimmermann, Camilla and Marc, and Dion Lee have demonstrated international market penetration through strategic branding and digital visibility [57], while government and industry bodies including the Australian Fashion Council and Creative Victoria support innovation and export readiness [12,58]. Together, these conditions, namely high SME concentration, measurable digital adoption gaps, regulatory pressure, and an active support ecosystem, make the Australian fashion industry a theoretically appropriate and empirically tractable context for examining AI adoption.

This study employed a qualitative and exploratory research design to gain deep, context-rich insights into the implementation, challenges, and opportunities surrounding AI adoption within the Australian fashion industry. A qualitative approach was considered appropriate because the study aimed to explore complex and context-dependent processes of technological change rather than to test predetermined hypotheses [59]. It is important to note that the study does not formulate or test causal hypotheses; consequently, concerns regarding endogeneity, a condition arising when an independent variable correlates with the error term in a regression model, are not applicable to this qualitative, non-causal design. The aim is to generate theoretically grounded, context-specific insights rather than to establish causal relationships. The research design is theoretically grounded in the TOE framework, which serves as the deductive foundation for both data collection and thematic development. This method allows for the interpretation of meaning from participants' experiences and captures the organizational, cultural, and structural factors that shape technology adoption in creative industries [60,61]. Given the evolving and under-researched nature of AI integration in fashion, an exploratory design offered the flexibility to identify emergent themes and interpret varying perspectives across design, manufacturing, retail, and sustainability contexts [52,53]. This approach aligns with inductive reasoning principles, enabling theory generation grounded in real-world practices and the lived experiences of industry professionals [62,63].

3.2. Participants

Participants were selected through purposive sampling to ensure a broad spectrum of professional experiences and organizational contexts were represented. Participants were eligible if they held a decision-making or specialist role bearing on technology or sustainability, had at least 5 years' experience, and worked within an organization operating in the Australian fashion value chain. Candidates were identified through industry networks/professional associations/RMIT industry contacts and approached directly. Twelve were invited and nine consented. The sample was constructed to capture the technological, organizational, and environmental vantage points central to the TOE framework (from an AI-native start-up and independent SMEs to a global retailer and an ethical-certification body) rather than to achieve statistical representativeness. Table 2 presents the demographic distribution of interview participants.

Table 2. Demographic spread of the interview participants.

Participant Number	Role in the Australian Fashion Industry	Sector/Specialization	Business Type
P1	Founder	Fashion technology and AI innovation	Tech start-up
P2	Founder & Creative Director	Accessories design	SME
P3	Founder	Accessories design	SME

P4	Brand Strategist	Fashion branding and creative direction	Consultancy/Enterprise
P5	Sustainability Coordinator	Ethical production	SME
P6	Project Manager	Circular economy and textile recycling	Textile recycling/Manufacturing
P7	Manufacturing Specialist	Textile production and recycling	Manufacturing/Supply chain
P8	Program Director	Supply chain traceability and compliance	Ethical certification organization
P9	Planner/Merchandiser	Fashion retail planning and analytics	Global retail organization

Organizations in this sample range from individual consultants and SMEs to large global retailers, reflecting the study's focus on the full Environmental TOE context shaping Australian SME decision-making (see Section 3.1). Given this range, firm characteristics are reported descriptively rather than through a single standardized size metric.

The diversity in roles and business models enriched the dataset, providing a multi-dimensional understanding of how AI adoption manifests across strategic, operational, and creative domains. The sample size of nine participants was deemed appropriate based on preliminary thematic saturation appropriate to an exploratory design, a principle in qualitative research that indicates sufficient data has been collected when no new themes or insights emerge from additional interviews [62,63]. Recurrence of these core patterns (cultural hesitation, limited local technical expertise, and the pace of technological integration) was evident from approximately the seventh interview onward, after which further interviews produced variations on existing themes rather than new ones. We therefore claim preliminary thematic saturation for these recurring cross-segment themes, while acknowledging that single-participant segments, such as global retail and ethical certification, cannot be considered individually saturated and are treated as illustrative rather than representative.

3.3. Procedures

Data was collected through semi-structured interviews conducted via online video conferencing platforms. This method provided flexibility and accessibility, allowing participants from different geographical regions to contribute to the study. Each interview lasted approximately 30 to 45 min and was recorded with the participants' consent to ensure the accuracy of data capture.

3.4. Measures

The interviews followed a guiding protocol that focused on three key areas: (1) implementation of AI technologies within business operations, (2) challenges and barriers to adoption, and (3) opportunities and perceived future potential. To ensure rigorous theoretical grounding, the interview questions were derived directly from the constructs of the TOE framework. This linkage ensures that each question is anchored in established literature regarding technological relative advantage, organizational readiness, and environmental/regulatory pressures. This deductive approach allowed for a transparent connection between the literature review and the empirical investigation [59,60]. Coding was conducted by two researchers. Where two coded, a subset of transcripts was coded independently, and discrepancies were resolved through discussion until consensus. An audit trail of coding decisions was maintained, and reflexive memos recorded; interpretive peer debriefing was undertaken with the research team. Open coding generated approximately

three initial codes, which collapsed through constant comparison into the sub-themes reported in Table 3 and clustered under the three TOE dimensions.

3.4.1. Interview Protocol Development

This set of interview questions was specifically designed to examine the implementation, challenges, and opportunities associated with artificial intelligence (AI) in Australian fashion businesses. The question framework was adapted and expanded from Siddhu and Mohibi [64], who investigated AI adoption in the Indian fashion industry. The instrument of Siddhu and Mohibi provided the conceptual baseline. It was revised for the Australian context by replacing references to India-specific policy and market conditions with the Australian regulatory environment (the Seamless clothing product-stewardship scheme and the Modern Slavery Act 2018); adding probes on geographic isolation and seasonal inversion as adoption drivers, adding items on sustainability, circularity, and textile recycling to reflect local stewardship obligation; and removing items not relevant to Australian SMEs. Each item was then mapped to a TOE construct as shown in Table 3.

Table 3. Mapping of Interview Questions to TOE Constructs.

TOE Construct	Measure/Dimension Addressed	Interview Question
Technological Context	Industry discourse, adoption status, and technological drivers.	Q1, Q2, Q3
Organizational Context	Internal barriers, cultural/ethical challenges, and resource needs.	Q4, Q5, Q6
Environmental Context	Sustainability opportunities, external stakeholder roles, and market outlook.	Q7, Q8, Q9, Q10

3.4.2. Interview Questions

Technological Context

1. From your perspective, how is AI currently being discussed or explored within the Australian fashion industry?
2. Has your business or professional network considered or implemented any AI technologies? If so, what areas were targeted (e.g., design, retail, supply chain)?
3. What factors influence the decision to adopt or not adopt AI tools in your organization?

Organizational Context

1. What are the most significant challenges in implementing AI, whether technical, cultural, or ethical?
2. Are there any specific barriers you believe are preventing wider adoption of AI in Australian fashion businesses?
3. What kind of support (e.g., training, funding, policy guidance) would help fashion businesses implement AI more effectively?

Environmental Context

1. What opportunities do you see for AI to enhance business performance, creativity, or sustainability in fashion?
2. How do you think AI could support ethical or climate-conscious innovation in the industry?

3. In your view, what role should designers, entrepreneurs, or educators play in shaping the future of AI in fashion?
4. Is there anything else you'd like to share about your experience or observations regarding AI and digital transformation in fashion?

3.5. Data Analysis

To address the requirement for transparency in theme development, this study utilized a hybrid deductive-inductive approach. Data analysis followed the reflexive thematic analysis approach outlined by Braun and Clarke [65]. The emergence of themes followed a structured four-stage process:

- (1) Familiarization and Deductive Framework Mapping: Verbatim transcripts were reviewed against the three core pillars of the TOE framework (Technology, Organization, Environment).
- (2) Systematic Open Coding: Data segments were coded to capture specific industry nuances, such as creative hesitation or regulatory anxiety.
- (3) Thematic Clustering linked to Literature: Codes were clustered into potential categories based on themes identified in the literature review, such as the 'black box' paradox (Technological) and sustainability mandates (Environmental).
- (4) Refining and Proposition Linking: Emergent themes were reviewed to ensure they were directly linked to the research questions and theoretically grounded. For example, the theme of passive adoption emerged from the intersection of Organizational constraints and Technological complexity.

This systematic process demonstrates how the themes did not emerge in a vacuum but were developed as a direct response to the gaps identified in the literature review, specifically the need to interrogate the socio-technical barriers in the Australian context. The final themes were structured according to the three contextual dimensions of the TOE framework: Technological, Organizational, and Environmental.

4. Findings

The thematic analysis of nine semi-structured interviews demonstrates that AI adoption within the Australian fashion industry is shaped by a complex interplay of technological, organizational, and environmental factors. Table 4 consolidates participant perspectives into three overarching themes and their corresponding sub-themes, structured according to the TOE framework. The following sections interpret each theme in depth through participant evidence.

Table 4. Summary of overarching themes and sub-themes identified in thematic analysis.

Overarching Theme	Sub-Themes	Analytical Focus
Technological	Implementation	Fragmented, functional, and third-party adoption through vendor-embedded AI systems.
Organizational	Challenges	Cultural resistance, creative hesitation, and leadership fatigue constrain digital transformation.
Environmental	Opportunities	Efficiency, personalization, and sustainability as emerging drivers of future competitiveness.

4.1. Implementation: Fragmented, Functional, and Third-Party

AI integration across Australian fashion businesses is fragmented and largely functional rather than transformative. Participants described adopting AI through embedded features of existing platforms instead of purpose-built strategies. P3 explained that “Shopify is our website, Klaviyo is our email system... all of those have got AI underpinning them,

it just comes with the program now." Most respondents used AI to automate marketing and operations. P2 stated, *"In the past we need to hire an agency that will require a retainer fee like \$1000 and it's on top of that. So, implementing AI is great. So instead of having an agent, we use AI."* P5 relied on an AI-powered carbon-accounting platform, describing it as *"a massive endeavor that helps us spend less time on compliance and more on the work that creates on-ground impact."* P8 reported using AI systems to *"verify data"* and *"automate traceability checks"* across supply chains, noting that *"We use AI tools to verify data in real time, which significantly reduced manual verification efforts."*

The use of AI for design or creative work was minimal. P2 stated, *"I prefer to stretch my brain; I want a good brain when I'm 80,"* and P3 resisted generative tools because they *"flatten individuality."* P4 observed that *"AI can be creative and strategic, but right now, people see it as a tool for marketing or analytics, not design."*

One exception was the AI-native start-up represented by P1, whose company developed a body-scanning and sizing algorithm. The participant explained, *"We recreate all your measurements and recommend your size across brands; returns dropped between 20 and 40 percent in pilot stores."*

Across all cases, AI was described as a support mechanism rather than a strategic capability, indicating that most Australian fashion businesses remain at an early stage of digital maturity.

4.2. Challenges: Organizational Culture

All nine participants identified cultural resistance rather than financial or technical constraints as the dominant obstacle to AI adoption. P1 remarked, *"We're a very risk-averse country... we like to follow. If everyone else has done it and it's a sure thing, then sure, that's our mentality."* P7 observed that companies *"don't want to do anything different; they'd rather stick to the same old practices,"* while P3 summarized the prevailing sentiment: *"If it's not broken, why reinvent it?"*

Cultural resistance manifested differently by firm size. Among the SMEs and founder-led businesses (P2, P3, P5), resistance was bound up with creative identity, limited founder bandwidth, and a pragmatic *"if it's not broken"* disposition. Among the larger consultancy and global-retail participants (P4, P9), resistance presented instead as transformation fatigue and the change-management load of moving a larger workforce. This distinction is consistent with the structural digital divide quantified by the ABS [54], in which scale, liquidity, and fixed adoption costs separate small from large firms.

Participants also highlighted transformation fatigue stemming from repeated digital transitions. P7 noted that *"the hardest part isn't the technology, it's the change management... that's where you get the most resistance,"* while P1 recalled that *"They've got so much to do. Everyone's burnt out... they're exhausted to set time aside to actually learn."* A shortage of local AI expertise compounded these issues. P7 said, *"I've probably been approached by one company in the last four years, there's nobody bringing solutions that actually solve our problems."* P8 added that most traceability platforms are *"built for global frameworks, not Australian regulations."*

Emotional and ethical apprehension further reinforced organizational inertia. P3 and P9 reported employee fears of job loss. P2 warned that *"AI makes us lazy, dulls our senses, and takes away individuality,"* while P4 reflected that *"data-driven decision-making can disconnect us from emotional design."*

4.3. Opportunities: Efficiency, Personalization, and Sustainability

Despite limited implementation, participants unanimously viewed AI as a powerful enabler of future competitiveness. P3 reported that *"AI saves so much time it automates tasks that used to take days,"* while P1 noted that it *"lets one person do the job of three to five people."*

P5 described how automation in environmental reporting “frees people to focus on strategic impact instead of data entry.”

Personalization represented another major opportunity. P1 explained that AI sizing tools can “solve the billion-dollar problem of fit and returns,” while P4 identified “huge potential in virtual try-ons and hyper-personalization.” P9 described using predictive analytics to “match products to local demand.”

Sustainability was perceived as the most significant unrealized opportunity. P9 argued that improved forecasting “could drastically reduce overproduction,” while P7 cited automated textile-sorting technologies that “detect fabrics and separate them for recycling.” P8 explained that AI “verifies and accelerates data audits.”

Participants also raised concerns about creativity and employment. P2 stated, “It makes people lazy; it dulls our senses, and we lose individuality,” and cautioned that the industry risks becoming “too reliant on convenience.” P3 observed that “there’s a fear that AI will replace junior roles,” while P9 noted that staff are “worried about being replaced by systems that can plan faster or cheaper.”

5. Discussion

This study examined AI adoption across nine Australian fashion businesses through the TOE framework, revealing that technological capability, organizational culture, and environmental pressures operate as distinct but interrelated forces shaping adoption outcomes. The following sections interpret the findings against each dimension of the framework.

5.1. Technological Dimension

Within the technological dimension of the TOE framework, readiness is typically understood as the degree to which a firm’s existing infrastructure enables or constrains adoption [48]. The findings suggest that while AI technology is present across most participating organizations, it is embedded passively within third-party platforms rather than deployed as a deliberate strategic capability. This aligns with AlSheibani et al.’s [51] passive adoption maturity model, where small enterprises engage with AI indirectly through vendor-supplied systems, limiting their ability to leverage it as a source of competitive advantage. Ortiz-Ospino [52] similarly found that firms dependent on external AI vendors achieve only incremental innovation outcomes, as they lack control over data architecture and model training.

The one exception, P1’s body-scanning start-up, illustrates what purposeful technological investment can yield. Angelbratt [66] and Ramos et al. [3] both document measurable reductions in return rates and logistics waste through AI-based fit technology, outcomes consistent with P1’s reported results. This contrast between passive and purposeful adoption underscores that technological readiness in Australian fashion is unevenly distributed and largely unrealized as a strategic asset.

5.2. Organizational Dimension

The organizational dimension of the TOE framework encompasses leadership, firm size, and internal readiness [50]. Traditional applications of the framework emphasize resource availability and infrastructure as the primary organizational determinants of adoption. However, the findings here indicate that cultural factors override these structural considerations. Status quo bias, transformation fatigue, and ethical apprehension emerged consistently across all nine participants as stronger inhibitors than cost or capability gaps.

Arangath [67] explains that psychological resistance rooted in fear of the unknown frequently leads organizations to avoid innovation even when the case for change is clear,

a pattern directly reflected in participants' accounts. The transformation fatigue described by P7 and P1 is consistent with evidence that repeated digital transitions increase employee burden and neutralize productivity gains when change is experienced as disruptive rather than enabling [68]. The emotional dimension, captured in P2's concern that AI "dulls creativity" and P4's fear of disconnection from emotional design, reflects what Manchiraju [10] termed ethical dissonance, and mirrors Marku's [21] finding that creative culture in fashion can override evidence of technological advantage.

This study therefore broadens the organizational dimension of the TOE framework by foregrounding mindset, creative identity, and cultural risk aversion as critical variables alongside the structural factors conventionally examined. In the Australian fashion context, organizational culture is not a secondary consideration but the primary determinant of adoption outcomes.

5.3. Environmental Dimension

The environmental dimension of the TOE framework encompasses external market conditions, regulatory pressures, and competitive dynamics [47]. The findings extend this dimension in two important ways. First, they confirm that regulatory and sustainability mandates are functioning as active adoption drivers, with participants citing compliance obligations and traceability requirements as motivators for AI investment. Second, they reveal that these pressures are not purely market-driven but ethically and socially constructed, shaped by consumer expectations, industry scrutiny, and government stewardship obligations.

Chen et al. [1] documented productivity improvements of up to 30% in fashion firms using AI analytics, consistent with participants' efficiency observations, while Karmali [69] found that machine-learning textile sorters improve fiber-recycling accuracy by over 90%, giving empirical weight to P7's vision of automated fabric sorting. Ramos et al. [3] reported a 25% reduction in human error in ESG reporting through AI, corroborating P8's experience of accelerated data audits. Rahman et al. [24] further found that AI-driven personalization enhances brand loyalty, reinforcing P4's observations about its commercial potential.

Taken together, these findings position sustainability not merely as an external compliance burden but as a strategic opportunity that environmental pressures within the TOE framework are beginning to activate. This expands the conventional understanding of the environmental dimension beyond market and regulatory forces to include the ethical and social construction of adoption incentives.

5.4. Ethical Dimensions and Responsible AI Integration

Interpreted collectively through the TOE framework, the findings position AI as a latent catalyst rather than an active driver of innovation in Australian fashion. Technologically, capability exists but is passively embedded. Organizationally, cultural resistance overrides structural readiness. Environmentally, sustainability pressures are emerging as genuine drivers but have yet to translate into widespread strategic adoption.

Jobin et al. [70] emphasize that responsible AI governance depends on transparency, inclusivity, and human oversight, suggesting that addressing the ethical concerns raised by participants is not peripheral but central to building the organizational trust necessary for deeper adoption. The sector's advancement will therefore depend on coordinated cultural, educational, and infrastructural reform that reframes AI not as an external utility but as an embedded creative and ethical partner, one capable of enhancing innovation, upholding human creativity, and accelerating the transition toward circular and responsible fashion systems [71].

6. Limitations and Future Research

This study provides critical empirical insights into AI implementation, challenges, and opportunities within Australian fashion businesses, yet six key limitations should be acknowledged.

First, the research was based on a small qualitative sample of nine participants. While this approach allowed for rich, contextual insights into organizational and cultural factors, it limits the generalizability of the findings across the wider industry [59]. Future research should adopt mixed-method or longitudinal designs, incorporating large-scale surveys or longitudinal case studies to test and extend these qualitative results [62].

Second, the study relied primarily on self-reported experiences, which may introduce interpretive or recall bias. As participants' perspectives reflect personal and organizational viewpoints rather than measurable outcomes, the data capture perceived meaning rather than objective performance [60]. Future studies should triangulate interview data with observational evidence or business performance indicators to evaluate the practical impact of AI adoption on innovation, productivity, and sustainability outcomes [60].

Third, the sample does not include representatives from Australia's top-tier fashion brands or from Indigenous fashion organizations. Top-tier brands operate with substantially greater resources and international market exposure, while Indigenous fashion enterprises navigate unique socio-cultural considerations around data sovereignty and cultural intellectual property [36,38]. The absence of these voices limits the generalizability of the findings to these segments, and future research should specifically target their experiences of AI adoption and resistance through dedicated studies of each group.

Fourth, this study does not systematically address the environmental cost of AI itself as a potential barrier to adoption within a sustainability-focused industry. The computational demands of training and operating large-scale AI models generate substantial carbon emissions, creating a paradoxical tension for fashion businesses motivated by sustainability imperatives [27]. Participants were not specifically probed on this dimension, and the extent to which awareness of AI's carbon footprint shapes adoption intent among sustainability-oriented Australian fashion businesses remains unknown. Future research should conduct a dedicated investigation into whether this "AI sustainability paradox" constitutes a meaningful barrier within this sector.

Fifth, data privacy regulation represents an underexplored environmental factor in this study. Australia's Privacy Act 1988 (Cth) and its recent reform, culminating in the Privacy and Other Legislation Amendment Act 2024 (Cth), impose evolving constraints on the data collection, storage, and processing practices that underpin many AI applications [72]. While participants referenced transparency and compliance as concerns, the specific implications of domestic privacy law for AI adoption strategy were not deeply explored. Future research should conduct a dedicated data-governance study examining how evolving privacy frameworks shape AI investment decisions within Australian fashion SMEs.

Finally, the findings highlight a capability and ethics gap that warrants further investigation. Sustainable AI transformation depends not only on technological readiness but also on building human capability, ethical oversight, and institutional trust [73,74]. Future studies should explore collaborative university–industry capacity-building models involving policymakers and fashion enterprises to enable responsible and culturally aligned AI innovation in the Australian fashion sector.

7. Conclusions

This study provides an empirical overview of AI adoption within Australian fashion businesses, showing that current implementation remains limited and primarily facilitated through accessible, third-party tools supporting marketing, basic analytics, and operational tasks. Advanced applications such as predictive forecasting, generative design, and intelligent inventory systems are largely absent, reflecting an early and uneven stage of adoption across the sector. The findings identify organizational and cultural barriers, particularly risk aversion, resistance to change, and limited digital literacy as the most significant constraints, outweighing cost or technical challenges commonly cited in existing literature. Despite this, the research highlights clear opportunities for AI to enhance business performance, including improved forecasting accuracy, reduced waste, operational efficiency, and strengthened sustainability practices.

The integration of the TOE framework provides a valuable theoretical lens for interpreting these dynamics. TOE clarifies how technological capability, organizational readiness, and environmental pressures collectively shape adoption decisions, helping explain the sector's uneven digital maturity and the influence of sustainability expectations and transparency demands. Overall, the study demonstrates that meaningful progress requires cultural and organizational transformation for AI to support long-term competitiveness and sustainability in Australian fashion.

Translating these findings into practice requires differentiated recommendations tailored to the structural realities of different enterprise types. For SMEs, which constitute most of the Australian fashion sector, the most impactful intervention is a tiered, low-barrier AI education program delivered through industry bodies such as the Australian Fashion Council and Creative Victoria. These programs should prioritize demonstrable, immediate ROI in cost reduction and sustainability compliance (for example, AI-assisted carbon accounting or automated order forecasting), rather than abstract capability-building. Government-backed digital adoption vouchers and subsidized pilot schemes would lower the financial threshold that currently prevents SMEs from trialing AI tools. For fashion technology start-ups, the priority is incentivized research and development partnerships with universities and research bodies such as CSIRO to develop Australia-specific AI solutions designed for the country's geographic constraints, seasonal inversion, and domestic regulatory environment, rather than repurposing global platforms that do not fit local contexts. For larger enterprises and global retail operations, the evidence points to a need for structured, leadership-driven change management programs that explicitly address transformation fatigue and create psychological safety for digital experimentation. Formalized internal AI champions, cross-functional digital literacy workshops, and transparent communication about how AI tools complement rather than replace human roles are the mechanisms most likely to shift the cultural inertia identified in this study. Across all firm types, practitioners and policymakers should foreground AI's direct link to sustainability compliance outcomes under schemes such as the Seamless product stewardship program, reframing AI investment not as discretionary innovation expenditure but as a prerequisite for long-term regulatory license to operate.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ML	Machine Learning
CV	Computer Vision
NLP	Natural Language Processing
GAN	Generative Adversarial Networks
SME	Small Medium Enterprises

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