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Adding External Artificial Intelligence (AI) into Internal Firm-Wide Smart Dynamic Warehousing Solutions

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Abstract: This study advances knowledge in the AI field. It provides deep insight into current industry generative AI inclusion systems. It shows both literature and practical leading industry operations can link, overlap, and complement each other when it comes to AI and understanding its complexities. It shows how to structurally model and link AI inclusions towards delivering a suitable sustainability positioning. It shows approaches to integrate external AI contributions from one firm into another firm's intelligences developments. It shows how to track, and maybe benchmark, the progress of such AI inclusions from either an external or an integrated internal software developer perspective. It shows how to understand and create a more sustainable, AI-integrated business positioning. This study considers firm artificial intelligence (AI) and the inclusion of additional external software developer engineering as another AI related pathway to future firm or industry advancement. Several substantive industrial warehousing throughput areas are discussed. Amazon's 'smart dynamic warehousing' necessitates both digital and generative ongoing AI system prowess. Amazon and other substantive, digitally focused industry warehousing operations also likely benefit from astute ongoing external software developer firm inclusions. This study causally, and stagewise, models significant global software development firms involved in generative AI systems developments—specifically ones designed to beneficially enhance both warehouse operational productivity and its ongoing sustainability. A structural equation model (SEM) approach offers unique perspectives through which substantive firms already using AI can now model and track/benchmark the relevance of their prospective or existing external software developer firms, and so create rapid internal 'net-AI' competencies incorporations and AI capabilities developments through to sustainable operational and performance outcomes solutions.

Keywords: artificial intelligence; assimilation; acquisition; digital network; generation AI system; transformation; innovation; sustainable performance; autonomous robots; deep machine learning; competitiveness; collective knowledge; strategic risk; productive capacities

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1. Introduction

Today, firms and corporate entities rely on their own intelligence gathering to differentiate themselves and to remain closely in-tune with their marketplace and its rules, their rivals, and with the dynamic consumer demands experienced across their globally competitive environments.

This study considers smart business and corporate entities (hereafter termed 'firms') engaging in, choosing, and adopting, smart data capture. It considers emerging artificial intelligence (AI) trends. It elucidates AI-related competitiveness opportunities likely gained by early firm adopters. It assesses warehousing AI adoption by leading-edge firms. It offers future smart and dynamic strategic adoption pathways for a firm when it considers engaging external software developer firms to help it in the pursuit of specific and desired AI-related ongoing software enhancement inclusions. This model-based recognition system can guide a firm's focus when choosing a specific, desired mix of relevant external AI competencies and AI capabilities as internal firm enhancement additions.

1.1. Historical Flow of AI

In 1935, Alan Turing, an English mathematician, computer scientist, logician, cryptologist, philosopher, and theoretical biologist, first proposed an abstract computing machine with limitless memory, linked with a scanner that moved back and forth through memory, symbol-by-symbol, reading what it found and writing further symbols. The scanner actions were dictated by a program of instructions that was also stored in the memory in the form of symbols [1]. Turing's genius framed the pathways for modern computing and produced insights into what is now known as AI [2].

In 1952, Christopher Strachey delivered an early AI algorithm that played checkers on a Ferranti Mark1 computer, and Anthony Oettinger delivered a machine learning 'Shopper' program on an EDSAC computer that sourced one item from a group of other mixed items, and then recalled in which of the eight shops along with the position it was located.

Thus, AI from early days of computing began to add 'smart' general intelligence components. Today, these AI 'smart' intelligences extend into machine capabilities, or into executing tasks like pattern recognition, decision making, and/or into making astute weighted judgments like humans. However, AI is extending further, and is assisting to upskill data-smart robotic machines towards possessing real-time 'dynamic' response capabilities that approximate human intellectual and behavioral ability, whilst also facilitating greater human resolution and actioning powers.

1.2. AI Advancement

Today, AI is an enabling digital data science. It is enabling computers or computer-controlled machines to think, act, and/or behave akin to the intelligent processes of humans [1]. The Oxford Dictionary defines AI as 'the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making, and translation between languages.' Thus, AI is a broad reaching mix of coalescing capabilities that can be designed to target specific physical or virtual fields to meet specific requirements and to deliver useful outcomes.

Chen et al. [3] suggest AI development has multi-faceted technologies, device controlling/manipulating algorithms, and consumer demand-related links into an ongoing sustainable position. Rakha [4] links significant AI opportunities to multifaceted data quality, accessibility, rules consequences, and equitable benefits and their effect on an ongoing sustainable position. Van Wynsberghe et al. [5] add AI interoperability, networking, and reusable algorithms can contribute to ongoing sustainability performance and operational costings. Kindylidi and Cabral [6] complement these comments adding consumer interest in information also grows AI's importance in delivering both consumer desired products and services, and in-turn affecting the ongoing sustainability position and the sustainable AI-related lifecycle. Thus, AI remains a complex, multi-faceted network of costly interacting and directing intelligences, that in business, can impact consumers in their demands for products and/or services.

Like the above directions, firm AI inclusion is widely literature-supported as a stage-wise, developmental, intelligences-driven, change process [7,8]. Identified benefits that AI inclusion offers the firm include (1) collations of knowledge-driven competencies and capabilities; (2) engaging innovative digital deep learning; along with (3) robust stage-wise interpretations, and these effects ultimately network, and coalesce towards possibly delivering beneficial competitiveness changes [9].

Today, AI has moved from mildly intelligent data manipulation towards highly complex global data fusion, sensory capture, behavioral interpretation, extended realities, and clever self-learning across internet-of-everything integrated devices/systems [10].

1.3. Generations of AI Systems Development

Currently, AI's development has delivered up to generation 4 AI systems, and there is ongoing progression towards an imagined further six more generations of AI systems development [11–13].

The first five generations of AI are (1) simple reactive AI systems using basic digital information and programmed to deliver specific responses in an unsupervised non-learning manner; (2) AI systems using basic machine learning to compare past/present data and to use predictive algorithms to project required changes or redirections; (3) detailed limited combinations of input-sourced AI machine learning systems that can combine data capture and then read, interpret, and sometimes develop, specific real-time responses that improve reliability but cannot improve functionalities against the experiences collected; (4) AI systems and smart autonomous robotics with more advanced deep learning scenarios, global data gathering, detailed fluidity-of-thought, intelligent memory processing/recall management, and smarter decision making that can adapt findings towards appropriate (and even future-forecasting) communicative interactions; and (5) AI systems operating super-intelligently as dynamic, self-aware, emotionally conscious, intelligent brain-like, multi-interacting neural entities that perceive/interpret/resolve/adapt to almost anything in a human-like manner [11–13].

1.4. Current Generations of AI Applications

Facebook, Google, and now Microsoft, are key software developers behind AI's rapid advancements. Over the past five years, Microsoft has reportedly invested USD 13 billion in OpenAI and launched generation 3 AI ChatGPT, and then generation 4 AI ChatGPT, into answering in-depth consumer queries/questions. It now leads Alphabet (Google) and META (Facebook) in this field. Australian firms like the Commonwealth Bank have deployed Chat GPT AI solutions to recognize and block scams and to reduce payment anomalies—saving its consumers over AUD 250 million. The telecommunications firm Telstra uses ChatGPT solutions to provide precise enquiry summaries and has reduced consumer call times by 20%. The paint manufacturer Cabot's has deployed its own consumer Chatbox to respond to queries around its woodcare products.

Today, humanoid (human-like) robots like Ameca, Sophia, and Apollo use large language models like ChatGPT, Microsoft Copilot, and Google Gemini approaches and are improving these, with their generation 4–to–5 AI systems moving closer to realistically mimicking deep human actions, expressions, and behaviors, but so far, unlike humans, these humanoids cannot cry or bleed. Such leading-edge robots coalesce AI, global database assessment, and advanced materials/mechanics into their capabilities. Many other developing forms of autonomous robots are now following, and these are generally being deployed to work in specific or designed operational environments. Still, other large language models are also available, including GPT-4 Turbo and Nvidia Hugging Face/ServiceNow's StarCoder2 LLM. Further, some smaller language models, like Vicuna-7B, Nvidia's Chat, and Retrieval Augmented Generation, can now run on specific smartphones. These too can incorporate into the firm's ongoing and mobile intelligences developments.

Neuralink, an Elon Musk company, aims to 'create a generalized brain interface to restore autonomy to those with unmet medical needs today, and unlock human potential tomorrow.' It is creating its own breakthrough generation 5 AI systems technologies using brain implants to monitor/digitally stimulate/drive ongoing brain messaging activities.

In February 2024, Neuralink.com successfully used its own robotic surgery to implant 1024 electrodes across 64 connections into a human's brain, and the testing phase is now underway. Neuralink.com's goal is to deliver generation 5 AI system symbiosis with human intelligence, and to use directed thought to directly action external devices. Another aim is to deliver spectrum-wide vision capabilities that extend and enhance human sight capabilities. It is also working towards solutions that can solve or enhance body limb actions—like resolving and rectifying an inability to walk. Thus, generation 5 AI is a future possibility for companies like Neuralink, and others mentioned above.

1.5. AI and Mining

AI extends into mining. 'Gudai-Darri,' Rio Tinto's most technologically advanced iron ore mine (operational since April 2019), engages over one hundred AI-supported digital technologies [13]. This 'mine-of-the-future' applies AI to all levels of mine operation complexities, and across generation 1–to–5 complexities of AI. Rio Tinto aims for this mine site to operate under digital control, correct all iron ore mining functions, and rail haul shipment anomalies in a millisecond, and do so without the need for continual, ongoing human intervention [13]. Rio Tinto continues to advance its generation 1–to–4 AI-supported systems, and it remains focused on advancing its generation 5 AI-supported systems. It is particularly targeting coalescing superintelligence, self-awareness, emotional consciousness, and sensory AI capabilities into super-astute generation 5 AI solutions. Into the future, this Rio Tinto focus for its mines may even surpass human intelligences, further augment existing autonomous and intelligent robotics functionalities/flexibilities, in addition to likely driving advances in self-optimizing, predictive, problem-solving analytics activities [13].

1.6. AI and Warehousing

Similarly, AI extends into warehousing, where corporate entities like Amazon are designing ultra-efficient warehousing, and with minimal (ideally none) human input. Amazon's web services use generation 1–to–4 AI-enabled intelligent robotics complete with machine vision. Amazon's generation 3–to–4 AI machine deep learning capabilities systems are also grouped, packaged, and offered for purchase by other firms with less advanced integration capabilities. These Amazon web services recognize, sort, and inspect diverse items/goods, and they can extend AI into packaging, loading, and shipping to consumers or delivery to the marketplace. This AI-enabled robotics focused approach is likely to advance further with more advanced, self-learning, humanoid AI robots—like Tesla's 'Optimus Gen 2' bot, now trialing under selected industrial localities and possibly moving Amazon's smart warehousing closer to an autonomous 'warehouse-of-the-future' operation like that of Rio Tinto in mining.

1.7. AI and Pharmacy

In the pharmaceuticals industry, smart dynamic warehousing is likewise important—especially for large national operations and especially for those running low-cost warehouse models [14]. Today, Australia's largest retail pharmaceuticals employer—My Chemist/Chemist Warehouse Group, employs over 14,000 staff across over 550 retail outlets and eight warehouses. It enlists over 6500 servers and over 2000 mobile devices across its vertically integrated 24/7/365 yearly operation. Its warehouse and retail operations now interface smart phone technologies to capture damaged or faded barcodes and so greatly improve staff efficiency whilst reducing task completion times. In 2023, it added its digital health/wellbeing camera sensor scanner AI to measure heart rate, respiration, SpO2, and HRV, and provide predictive insight. It is progressing towards a single scalable operation that can seamlessly, reliably, and intelligently platform, whilst also running any application at store, warehouse, datacenter, or in-cloud levels. This involves partners such as AWS and IBM working with VMware and allowing virtual machines to operate with great degrees of automation and to datacenter orchestrate AI application movements within warehouse premises and engage vendor-respective public clouds. Today, this pharmacy group is incorporating various generation 1–4 levels of AI systems into its operations.

1.8. AI and Retail

Across the e-commerce sector, Walmart, the largest global retailer, with sales over USD 573 billion in 2022, competes with Amazon (sales over USD 512 billion in 2022). Its fulfillment centers, and its 4700 plus stores, and its 5000 internationally placed stores now offer automation, 24/7/365 service, and consumer variety of choice selection.

Marketplace Plus suggests Walmart's number of active e-commerce sellers is around one tenth that of Amazon's more than one million active sellers. However, in the US, most consumers live within 10 km of a Walmart store. This proximity advantage potentially offers a shorter delivery time than Amazon. Further, Walmart's website app has a consumer-perceived usability advantage. This means, Walmart remains competitive, and continues to advance its technologies, its automation, and its autonomous robotics deployment. In 2022, it invested USD 14 billion into innovation across its automation, technologies, supply chain, logistics, drone delivery, and consumer-facing initiative domains. These innovative directions are heavily linked into Walmart's generation 1–to–4 AI systems adoption and integrated with its ongoing store and fulfillment center autonomous advancements.

1.9. AI Systems Directions

Hence, and depending on the entity, or the field of business, or the person, and/or the operational or behavioral requirements, AI typically collectively resides across multiple generations of AI systems, and currently, AI development is progressing rapidly towards generation 5 AI systems, towards super-intelligence, and towards smart autonomous robotics and logistics systems.

This study now directs its attention to AI and warehousing. Warehousing is a key operational and logistics cost factor in all the above examples. Warehousing in mining uses AI to efficiently collect, store, and mix (as required) different raw material stockpiles into specifically demanded shipping blends to enable optimal performance at downstream processor sites. Warehouse distributors and retailers like Amazon deploy AI, automation, and robotics to deliver lower cost and rapid-supply operations. Warehousing in pharmacy uses AI to ensure products are efficiently stored, processed, packaged, and shipped downstream according to specific precise volume usage, or according to real-time projected consumer demand trends. Large retailers like Walmart use their in-store warehousing and fulfillment centers to conjointly, and efficiently, deliver consumer-demanded items in near real-time.

This study proceeds to show how global software developer firms can be modelled and better matched towards another firm's ongoing AI related internal warehousing requirements. It uses Amazon and three other warehousing approaches as its primary example.

2. Materials Used by Amazon across Its AI Warehousing

Warehousing today demands ongoing innovation moving it towards a 'warehouse-of-the-future' status. This resolves, schedules, compiles, delivers, and ships consumer-packaged solutions in an 'instant.' Hence, future warehousing likely involves data driven solutions combined with ongoing innovation, continuous latest technologies incorporations, smart dynamic AI incorporations, new fulfillment agilities, and more precise resource(s) utilization. Such approaches are also likely designed to capture continual growth in stock placement units and in most efficient logistical process pathways that then intermix smaller batch units and deliver unique consumer-ordered requirements. These features likely unlock against tight just-in-time supply chain availability, less skilled labor requirements, and ongoing increases in costs.

2.1. Smart Dynamic Warehousing

Over time, previous 'community storerooms' have progressed into multi-million dollar temporary-holding facilities called warehouses. Smart warehousing is a German high-tech strategy specifically formulated during the fourth industrial revolution [15]. It enlists digitally coordinated, computer and cloud digitally networked systems, bringing together coordinated AI systems IoT relevant items (and their automation), and delivering precision processing [15].

By 2018, most warehouses engaged some level of automation across their placement, storage, and retrieval operations, and this approach builds IT (information technology) knowledge and saves costs [15]. Today, rivalry and competition are driving continual efficiencies upgrades and supply chain/demand chain collaborations across the warehousing system [16–18].

Smart warehousing is claimed to be the most effective and efficient way of improving a firm's return on investment, improving precision processing, and reducing labor costs [15], but in the case of small-to-medium enterprises (SMEs), investment costs, uncertainty about costs, and lack of expertise may affect their overall industrial utilization of AI and robotics [19].

Today, *smart warehousing* defines as machine- and AI-directed raw materials and manufactured items inputs, their autonomous movement to specific rack and pick locations, and their packaging and shipping, with process intervention and tasking roles no longer human dominated. Thus, smart warehousing is technologies and process focused, but this form of warehousing can also be dynamic.

Dynamic warehousing adds instant change options and flexibility to the operation. This requires greater warehouse 'extended-input-to-extended-output' adaptability, combined with real-time adjusting, change-optimized agilities, and adjustable layout solutions. Dynamic warehousing is real-time consumer- and marketplace demand responsive, and it optimally operates beyond inputs/outputs. It optimizes space, applied robotics, automatic and autonomous systems and processes under specific generation 1–to–4 AI systems and solutions guidance.

Today, *dynamic warehousing* defines as autonomous input, and most efficient rack/picking storage, along with demand-optimized selection, and most efficient processing of specific demand output item(s). Thus, dynamic warehousing is a digital intelligences and real-time demand-process optimization solution.

Currently, smart warehousing and dynamic warehousing can combine their AI technologies, delivering 'smart dynamic warehousing' outcomes that assess options, operate in real-time, and delivers efficient decision making and agile solutions. Thus, smart dynamic warehousing incorporates developing AI digital intelligences and actioned roboticized capabilities as real-time item process optimization solutions that combine intelligences from suppliers across the entirety of warehouse-applied technologies and processes and through to the marketplace and its consumers [20].

Hence, *smart dynamic warehousing* is likely integrated, automated, and where possible, deploying autonomous robotic machinery. Such warehousing must real-time integrate operational and autonomous software, have active 3D mapped cell volume and space position recognition and translocation capabilities, provide shortest intralogistics flows real-time consumer connectivities, and selectively engage optimal, automatic, autonomous, and 3D laser-guided vehicle tasking, and consumer driven demand solutions.

2.2. Amazon: Delivery Methods Engaged in Smart Dynamic AI Warehousing

Currently, Amazon is arguably the largest and most advanced global, smart dynamic warehousing corporation. This study now considers Amazon from its inputs through to its marketplace and its consumers, and then against a software developers' perspective.

Amazon accepts from its suppliers and its just-in-time stores, over 14 million different item bins in each of its localized fulfillment warehouses, with each binned item's position within the warehouse allocated into a specific pod. It operates its warehousing model incorporating data collation, analysis, agile solutions, and deployment of its procurement/deliverance (digital and/or physical) system as a real-time flexible, scalable, most efficient, and costs minimized platform. Currently, Amazon deploys robots and more advanced AI in about 25% of its 160 plus global fulfillment centers. It estimates that by 2030, fully autonomous warehousing may be possible [21].

AI extends into warehousing, where corporate entities like Amazon are designing ultra-efficient warehousing, with minimal (ideally zero) human input. Its Amazon web services packages generation 3–to–4 AI machine deep learning capabilities systems. These can be purchased by other firms with less advanced integration capabilities. These AWS can recognize, sort, and inspect diverse items/goods. They can extend into packaging, loading, and shipping refinements, enabling faster firm connection into marketplaces.

Lindsey [22] believes 'intelligent technologies are automating data analysis to help organizations save time and money.' She considers human experience at Amazon and links it to AI developments, suggesting this fusion improves consumer outcomes, optimizes selection, and automates logistics. Amazon continues to add further AI systems -like its Alexa voice service, its Amazon Go stores, its ever-developing AWS, and its cloud computing, to further enhance IT automation and autonomous AI solution deliverables, and to bring its machine learning technologies across its procurement solutions.

Today, these AI systems also spread throughout real-time intelligent tracking and strategic planning, automation, spend optimization, suppliers, management, compliance, search results, and tail spend (faster servicing, easier processing, and precise discovery of best-pricing products). These all deliver growth in procurement, productivity, agility, and diversity of real-time deliverables solutions.

2.3. Amazon: Delivery Systems Engaged in Smart Dynamic AI Warehousing

Amazon engages multiple procurement, process, agility, and delivery systems across its networked warehousing operations. Considering current generative AI (real-time processing that learns patterns, re-structures data, computes and generates text, images, commands, or other remapped data in response to various requirements or prompts) approaches, Amazon applies these into its varied multi, intertwined, digitally related operational solutions. Table 1 shows 36 recent process applications mapped against its appropriately deployed generation 1–to–5 AI technologies solutions. Figure 1 presents a selection of relevant available Google images highlighting and visualizing AI-relevant aspects of each Table 1 application process.

Table 1. Amazon AI-deployed application methods and generative AI system levels applied.

Thirty Six of Amazon's Generative AI Deployment Methods	Gen 1	Gen 2	Gen 3	Gen 4	Gen 5
1. Architecture integration platform	x	x	x	x	x
2. Global big data engagement	x	x	x	x	x
3. Infrastructure & 2023 Trainium2 advanced cloud	x	x	x	x	x
4. ML augmented AI	x	x	x	**AI**	
5. ML stage details	x	x	x		
6. Deep AI monitoring	x	x	x	x	**AI**
7. Task specific virtual selection	x	x	x	**AI**	
8. Contacts analysis	x				
9. Large language models	x	x	x		
10. Virtual innovation	x	x	x	x	**AI**
11. Robotic process parcelling/delivery	x	x	x		
12. Autonomous language & ML processing	x	x	x		
13. Digital field-action simulation training	x	x	x	**AI**	**AI**
14. Warehouse SageMaker S/W	x	x	x	x	**AI**
15. SageMaker ongoing S/W enhancement modelling	x	x	x	**AI**	**AI**
16. Virtual fashion modelling	x	x	x		
17. Automated 3D stacker cranes & dynamic shelving	x	x	x	**AI**	
18. On-sold AI developed technologies	x	x	x		
19. External clouds integration	x	x	x	x	**AI**
20. External values-advancing partnering	x				

Table 1. *Cont.*

Thirty Six of Amazon's Generative AI Deployment Methods	Gen 1	Gen 2	Gen 3	Gen 4	Gen 5
21. Warehouse-of-Future layered-techs/innovative plant layout/design	x	x	x	x	**AI**
22. Optimized automated guided vehicles & trajectories	x	x	x		
23. Laser guided vehicles & drones	x	x	x		
24. Drone 3D-mapped external delivery service	x	x	x	**AI**	
25. Digital virtual warehouse & robotics autonomy	x	x	x	x	
26. Digital Twin—AWS IoT TwinMaker	x	x	x	x	**AI**
27. Autonomous warehouse robots	x	x	x	x	
28. Remote VR warehouse monitoring	x	x	x		
29. Supply chain visualization	x	x	x		
30. Holistic digital warehouse management system	x	x	x		
31. Integrated virtual management system	x	x	x	**AI**	
32. Virtual e-commerce system	x	x	x	**AI**	**AI**
33. Logistical warehouse activation	x	x	x	x	**AI**
34. Block chain quality connectivities	x	x	x	**AI**	
35. Advancing against external competitiveness	x	x	x	**AI**	
36. Sensory autonomous humanoid intelligence	x	x	x	x	**AI**

Bold '**AI**' = key ongoing development areas.

Table 1 indicates Amazon remains in active pursuit of improved real-time warehousing solutions, and it continues to develop the applications of higher generative levels of AI into its operational prowess.

Today, Amazon's AI is predominantly focused on operating towards, or at, generation 4 AI process levels, and its competencies-supported new assimilation, transformational, and acquisition abilities continue to advance within and across all four of its 1–to–4 AI generations. For example, Amazon's new Prime Air robotic delivery drone (MK30) adds another dynamic capability to its warehouse shipping by facilitating the delivery of small items into the warehouse's nearby consumer marketplace. This direct point-to-point flight technology networks across many AI areas. First, it can acquire energy from home-base renewable chargers. It can read, pickup, ship, and location-deposit a parcel or item. It can engage a GPS laser guidance system. It can real-time recognize and carry specific items of up to 5 lbs. in collective weight. It can fly for up to one hour, 3D position its consumer-intended parcel or item, and then return to home-base. Across one year, it can make thousands of flight deliveries—and in most weather conditions. Its payloads can vary across thousands of possible items—such as batteries, drugs, books, beauty products, etc. The MK30 also has a degree of autonomy when positioning deliveries and when communicating with its external or virtual controllers.

Under generation 4 AI, the above features and other Amazon AI factors combine towards providing ever-smarter delivery efficiencies, greater corporate agilities, faster precision delivery, lower costs, and higher decarbonization per item delivery.

Machine language, another vital Amazon smart warehouse component, brings machine learning and optimizing algorithms into each warehouse process. For example, machine language learning is continually advancing and incorporating generation 4 AI. Techniques like forecasting/projecting consumer demand versus past data, personalizing communications by tracking favorites and product choices, and robotic activities/use-optimizations by item logistical/direct delivery servicing, when coordinated and intelligently interlinked, all coalesce to help advance Amazon's throughput process efficiencies [21].

Table 1 and Figure 1 indicate how Amazon is applying available latest technologies to enhance and cost minimize operations. Table 1 shows Amazon selectively matches and applies differing generative AI levels into each of its different process requirements. Those with minimal requirements tend to require simple solutions. Those with complex engagement requirements need more complex, and sometimes platform-networked solutions.

For example, in transportation of foods, software-coalesced development of manufacturing and supply chain systems can save time, costs, efforts, logistics, and provide faster delivery. This is now engaging Amazon's transparent block chain (image No. 34) for historical location, harvest, shipping, and quality information. So where to next?

Amazon relies on its digital prowess, and this likely requires astute ongoing software development. Hence, this study now considers how Amazon's competencies and capabilities can best retain and maybe advance both its sustainable operational and sustainable performance outcomes (image No. 30).

Table 1 shows (as an 'x') Amazon's generative AI engagement across its operational processes. All warehouse areas have AI embedded to some degree across the current range of generation 1–to–5 AI incorporations, and these areas are continually developing towards (or across) the generation 5 AI systems level.

For example, 'virtual fashion modelling' (image No. 16) houses measurement, fit shape, 3D rotatable images, and is a generation 3 AI system. In the future, virtual fashion modelling can house a virtual 'twin' image (image No. 26) of a consumer image modelling the chosen garment in differing color, position, and location environments. Hence, this simplistic generation 3 AI system continues advancing in complexities and capabilities towards a generation 4 AI system.

Similarly, and considering AI, an 'optimized automated guided vehicle and trajectories' (image No. 22) situation is somewhat restricted by the active paths that robotic transportation vehicles follow (image No. 33) via logistical warehouse floor activation areas. This generation 4 AI system is currently focused on direct, efficient, and collision avoidance grid movement of specific bin items, but as warehouse intelligence and sensing increases (image No. 36), more autonomous generation 4–to–5 AI systems for vehicles can likely emerge.

Table 1 shows (as a capitalized 'AI') where Amazon and its AI incorporation is currently particularly focused towards incorporating further detailed enhancements. These generation 4 AI systems and generation 5 AI systems areas are likely ones potentially offering Amazon larger net benefits and a further future competitive edge within its active global business marketplace.

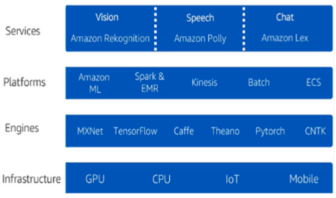
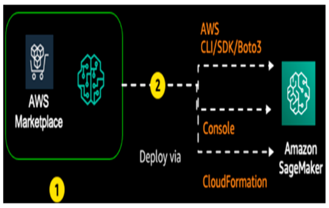
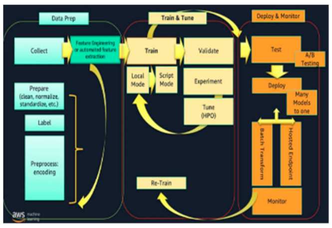
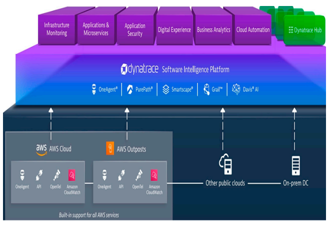
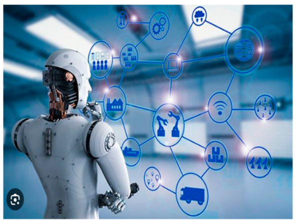
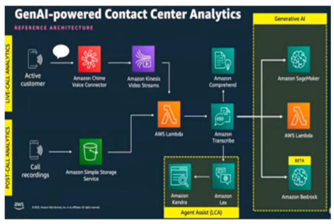
For example, movement towards a 'warehouse-of-the-future layered-techs/innovative plant layout/design' (image No. 21) requires high-level, coordinated, coalesced data. This helps support platform intelligent and software-driven capabilities advancement towards delivering required outcomes against its real-time generation 5 AI requirements.

Similarly, when considering 'supply chain visualization' (image No. 29), this is linked to the 'holistic digital warehouse management system' (image No. 30), which also encompasses the 'integrated virtual management system (image No. 31), and the 'virtual e-commerce system' (image No. 32). These generation 4 AI and generation 5 AI systems network and coalesce into components of a business platform that enables real-time and virtual management across Amazon's complete value chain, including external values-advancing partnering (image No. 20), and from anywhere and at any time.

Figure 1's visual aspect representation of components of Table 1's Amazon's generation AI-engaged operational processes gives further insight into complexities involved in delivering generation 5 AI incorporations. Every contributing pathway involves multiple networked integrations of data, analysis, and outcomes collations, with each further assessed against frameworks of efficient, flexible, agile, and precise speedy delivery actions.

For example, ‘delivery of field action simulation training’ (image No. 13) and ‘remote VR warehouse monitoring’ (image No. 28) requires operators to first become skilled in strategic risk management, digital autonomy, proactive skills capacities, collective knowledge, logistical perception, and digital creativity. These collective input competencies can then be network assessed and tested against relevant deliverable capabilities—with particular emphasis on the likely promotion of sustainable performance and/or sustainable operational advancement outcomes.

The following Figure 1 Amazon applications all require smart software development and networked collective integration. Many corporate entities and nations are currently in pursuit of techniques and measurable model approaches that best align AIrelated software input competency parameters into delivering ‘sustainable’ (for some time) AI software application output successes. Such AI software applications integrate and align AI across a business’ operational workflows and logistical systems. rather than contribute as just add-ons or standalone toolkit components. Thus, today AI brings an integral value, adding costefficient networking system into the corporate entity’s sustainability solutions.

1. Architecture integration	2. Global big data engagement	3. Infrastructure and 2023 Trainium2 advanced cloud	4. ML-augmented AI
			
5. ML stage details	6. Deep AI monitoring	7. Gen AI-task virtual selection	8. Gen AI contact analytics
			
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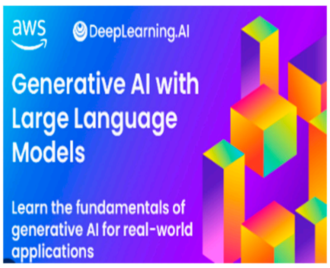	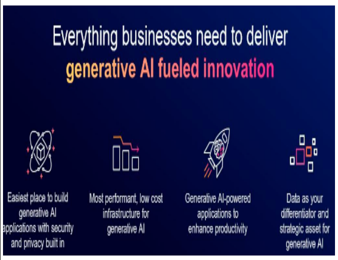	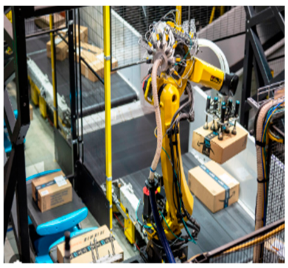	

Figure 1. *Cont.*

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<tr><td>13. Digital field-action simulation training</td><td>14. SageMaker S/W</td><td>15. SageMaker ongoing S/W enhanced modelling</td><td>16. Virtual fashion modelling</td></tr>
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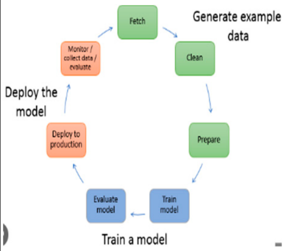
</td><td>
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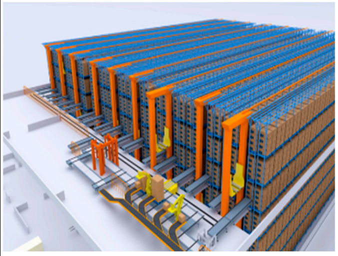
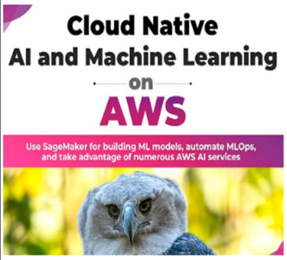
<tr><td></td><td>
</td><td>
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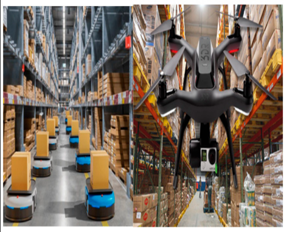
<tr><td></td><td></td><td></td><td></td></tr>
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<tr><td>29. Supply chain visualization</td><td>30. Holistic digital warehouse management system</td><td>31. Intgrated virtual management system</td><td>32. Virtual e-commerce system</td></tr>
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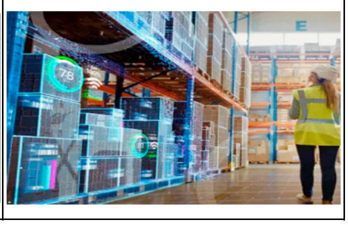
</td><td></td><td></td><td></td></tr>
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Figure 1. *Cont.*

33. Logistical warehouse floor activation	34. Block chain quality connectivities	35. Advancing against external competitiveness	36. Sensory autonomous humanoid intelligence
			

Figure 1. Thirty six of Amazon's warehouse deployed generation AI technology delivery methods/systems approaches (images sourced from Google's image collection).

The above Amazon applications all require smart software development and networked collective integration. Many nations are now in pursuit of techniques and measurable model approaches to best align software AI input competency parameters into delivering 'sustainable' (for some time) software AI output successes.

2.4. Literature Considerations

To model software developer firm AI contributions towards sustainability for a firm such as Amazon, we return to recent literature. Authors [23,24] suggest high sustainability standards can occur through AI and its (1) improved techno-scientific (or robotics-enhanced) qualities across production systems, (2) digital technologies integrated across productivity capabilities, (3) reduced production costs/emissions, (4) decreased intensity across production processes, (5) improved marketplace connectivities, and (6) expansive big data connectivities. Thus, AI has complex and multi-connected pathway contributions towards delivering sustainability.

Others [24] add these AI related processes further align and integrate (1) decision making processes, (2) human and artificial domains, (3) emergent technological changes, and (4) knowledge creation and so deliver beneficial sustainable business opportunities. A recent study [25] suggests incorporation of AI also requires system thinkers who (1) manage firm complexities, (2) design integrated strategies, and then (3) jointly leverage both AI transformational capabilities and sustainability outcomes. Some researchers [26] theoretically model and coalesce AI related competencies, including input resources, workforce capacities, creative big data knowledge, and technological adaptability into drivers of dynamic, flexible firm capabilities, which in turn collectively driver of a sustainable process system complete with feedback connectivities. These researchers [24–26] imply three-stage or multi-stage modelling is likely needed to investigate the role of AI in delivering sustainability.

Other researchers [27] believe digital transformation reshapes firm processes towards data-driven, intelligent, networked, and resilient AI-supported firm systems. This approach brings accuracy, precision, and efficient smart processes—complete with self-adaptability, reliability, flexibility, high-quality and low-cost output. Under this industry 4.0 AI-supported environment, model and computation investigations demonstrate achievability of minimal total cost and least machine energy consumption [27]. Thus, complex, combined digital approaches can offer AI efficient business processes and systems.

Hence, from differing perspectives literature and the above Amazon study each investigate AI inclusion as a net logical pathway towards enhancing a sustainability position. These differing perspectives coalesce and show AI typically operates as complex, integrated, digitalnetworked system incorporating intelligent decision making capabilities.

Further, AI builds upon an existing suite of firm possessed components that can incorporate relevant and developing AI components into the mix of available firm competencies. This paper interprets these competencies as risk management, digital autonomy, productive capacities, collective knowledge, and digital creativities. These competencies further support a downstream suite of actioned capabilities that can then optimally assimilate and/or transform and/or acquire networked new digital knowledge competencies into an actioned capabilities suite. This entire collective of AI advancement competencies and capabilities then supports a resultant more sustainable performance (and profitable) outcome, along with a resultant more sustainable ongoing operation. Thus, a three-stage (input, intermediate, output/outcome) multi-construct, causal, and networked investigative framework model (Figure 2) is envisaged as an approach to studying linkages between deployed AI and sustainability, and a SEM approach likely offers a bestchoice investigatory method.

Figure 2. Causal AI to sustainability-linked framework approach.

3. Methods

When delivering rapid software development, large business entities like Amazon often expand their internal software development and turn towards including the assistance of globally useful external software developer options. One tech-savvy country such business entities sometimes utilize is Pakistan. Pakistan sees itself as a value-adding contributor towards an engaged business entity's global software development solution(s).

Software development is one of Pakistan's five top global exports, and it is currently seeking to find enhanced pathways that help it improve, export, and expand key external software solutions. Hence, this study turns to SEM and quantitatively investigates how Pakistan's software development firms can further improve their international software developer deliverables and so create more sustainable global software developer business solutions for leading-edge, digitally astute clients such as Amazon, Rio Tinto, My Chemist/Chemist Warehouse Group, and Walmart. Hence, this study sees Pakistan software developer firms AI approaches across software development as being directly relevant to firms like those discussed above.

This 2024 study sources its information in conjunction with participating legal software developer firms registered through the Pakistan Government Ministry of Information Technology and Telecommunication Pakistan Software Export Board (refer Appendix A). These Pakistan software developer firms operate in the global and highly competitive developer marketplace. Today, this typically involves generative AI developments. Each firm also pursues its own strategic AI risk management competencies [28–32] and engages both its staff digital autonomies competencies and its available proactive capacities as competencies in pursuit of individual new AI and software approaches [33,34].

Within the AI domain, these software development firms use their collected knowledge competencies and their digital creativity competencies as input requirements that also include aggressive and global competitive competencies [35–40].

Today, registered software developer firms in Pakistan are typically involved in AI related projects, and their competencies suite is typically focused-towards actioning new AI transformational capabilities. This likely networks with their latest AI assimilation abilities capabilities and their current AI acquisition inclusions capabilities. This network of competencies and capabilities is only useful if it then delivers a net AI sustainable position for the individual software developer firm. This can AI measure as the software developer firm's sustainable performance and its sustainable operational outcomes. Hence, the Figure 3 framework for this study is established.

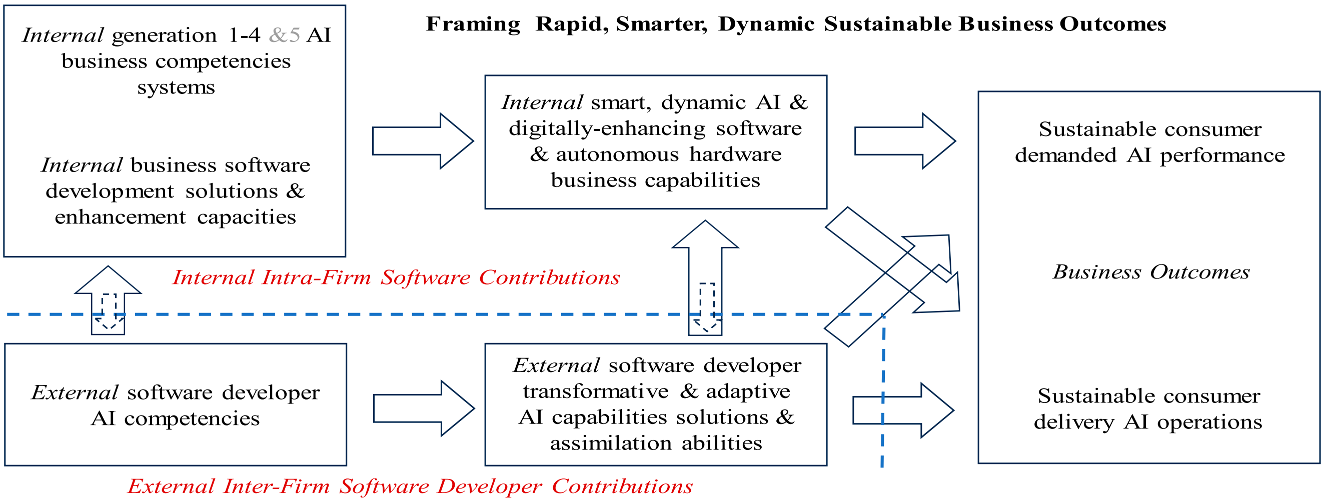

Figure 3. Study framework: external software development firm contribution pathways towards internal warehousing sustainability.

4. Analysis and Results

In pursuit of a likely expertise profile for software developer firms in Pakistan, this study first assesses its survey respondents' demographics. It then quantitatively builds the study's framework of competencies to capabilities to sustainability into a SEM pathways model approach. This model exposes how a software developer firm could ensure its skilled digitally focused workforce remains competencies and capabilities task aligned.

4.1. Survey Demographics

This January–February 2024 study quantitatively surveys, and then models, respondent data provided by 137 senior representatives of different (differing IP localities) leading and legal software development firms in Pakistan. Demographics show respondent age distributions are 76 (<30 years), 58 (30–45 years), and 2 (46–60 years), Respondent education levels attained are 70 (Batchelor), 59 (Master's) 4 (PhD), and 4 (other). Software respondent firm sizes are 7 (<10), 27 (11–50), 33 (51–100), 15 (101–200), and 54 (>200). Time in the industry is 0 (<1 year), 71 (1–5 years), 43 (6–10 years), 17 (11–15 years), 5 (>15 years). All bar four respondents have research and development roles ranging from analyst, to engineer, to programmer, to architect, to developer to manager, to QA manager. Hence, the survey data is deemed to suitably represent software developers, and information provided is deemed of an 'expert' and reliable nature.

4.2. Statistical Presentation of Quantitative Survey Software Develper Responses

The capture of software developer responses is gauged across ten resultant constructs. Three resultant factor-reduced question items (all residuals < 0.05), each with Likert scale (1 = strongly disagree to 5 = strongly agree) ranges, remain as the collective representation of one of ten framed constructs (refer Table 2).

Column 1 lists the three final factor reduced item measures for each construct [41,42]. Column 2 lists the construct load for each item. Experimental loads above 0.6 are acceptable in research, but those above 0.7 are preferred [43], and all bar four loads exceed 0.7. Column 3 lists the average variance extracted (or captured) by each construct relative to the amount of variance captured due to measurement error in the construct. The resultant values, as desired, all exceed 0.5 [43].

Table 2. Software developers' collated survey data table (compiled for Figure 3 and three-stage SEM modelling).

ELEVEN CONSTRUCTS, THEIR ITEMS, AND RELEVANT MEASURES	LOAD (λ)	AVE	CONSTRUCT MEAN (μ)	CONSTRUCT STD DEV (SD)	CRONBACH ALPHA (α)	LOADSD ($\sqrt{\alpha}$)	ERRORSD^2 $(1-\alpha)$
Company Staff Digital Autonomy		0.62	3.80	0.87	0.82	0.78	0.13
1. help develop strategic vision	0.884						
2. provide business ideas	0.787						
3. take part in developing business concepts	0.682						
Company Digital Creativity		0.63	3.83	0.76	0.84	0.70	0.09
4. supports staff creativity	0.881						
5. hire only employs who pursue creative ideas	0.855						
6. seek out new opportunities	0.617						
Company Quick Digital Innovativeness Response To		0.54	3.79	0.77	0.77	0.68	0.14
7. changes in consumer demands	0.783						
8. delivers new innovative services to consumers	0.745						
9. competitor initiatives	0.665						
Company Quick Proactive Capacities Response		0.84	3.80	0.99	0.94	0.96	0.06
10. offering best qualities for consumers	0.930						
11. delivering new innovations	0.911						
12. providing best products for consumers	0.901						
Company Strategic Risk Mgmt Assessed New Project Ideas		0.52	3.73	0.69	0.80	0.62	0.09
13. balance risk against financial rewards	0.816						
14. successfully manage associated risks	0.698						
15. bring unexpected beneficial opportunities	0.641						
Company Creative Collective Knowledge		0.64	3.97	0.74	0.86	0.68	0.08
16. combines external and internal knowledge to generate new ideas	0.813						
17. is shared to learn from other experiences and failures	0.801						
18. grows when specialist workforce skills are shared	0.783						
Company Sustainable Performance Outcomes		0.68	3.70	0.90	0.89	0.85	0.08
19. progressively increases its market share each year	0.885						
20. against last financial year remains superior to competitors	0.793						
21. competitors find it hard to gain competitive advantage against us	0.788						
Company Acquires New Knowledge By		0.59	3.92	0.73	0.84	0.67	0.09
22. regularly seeking consumers' feedback	0.786						
23. using routines that source/adapt/exploit new knowledge	0.771						
24. pursuing relevant strategic industrial intelligence information	0.737						
Company Assimilation Abilities Are		0.55	3.98	0.74	0.77	0.65	0.13
25. applied to its acquired information and knowledge	0.838						
26. proactively changing to changing market demands	0.775						
27. identifies new opportunities to provide quick service to customers	0.593						
Company Transformational Abilities		0.75	3.94	0.78	0.91	0.74	0.05
28. structurally help acquire new knowledge insights	0.898						
29. include employees sharing practical experiences	0.886						
30. continually refine our development of new products	0.816						
Company Sustainable Operations Outcomes		0.69	3.95	0.83	0.86	0.77	0.09
57. successfully exploit data/ideas/knowledge into software development	0.877						
58. effectively utilize operational knowledge into new software products	0.845						
59. effectively apply operational knowledge into new services	0.758						

Construct means are slightly positively skewed, and along with their respective SDs, are all suitable and within acceptable ranges for statistical analysis. All construct Cronbach alpha values are strong, and each is above 0.7, indicating sound construct internal consistency and scale reliability [43].

Each single indicator construct load and its individual construct error are calculated for structural equation analysis using Munck's equations [43–45]. Each load measure indicates strong loading on its individual single indicator construct, and combined with its individual (and small) error measure, these two measures collectively indicate each construct is likely suitable for maximum likelihood single indicator SEM analysis [44,45].

Single indicator SEM analysis is used when the construct's remaining factor reduction indicators items are closely related to the construct and have similar loadings, and when pathways across complex models are to be investigated. Then, the best representation of these similar indicators can likely be computed as an average (or weighted average) of the construct's remaining factor reduction construct items, rather than a selected item from this group [43–45]. This modelling is shown as Figure 4.

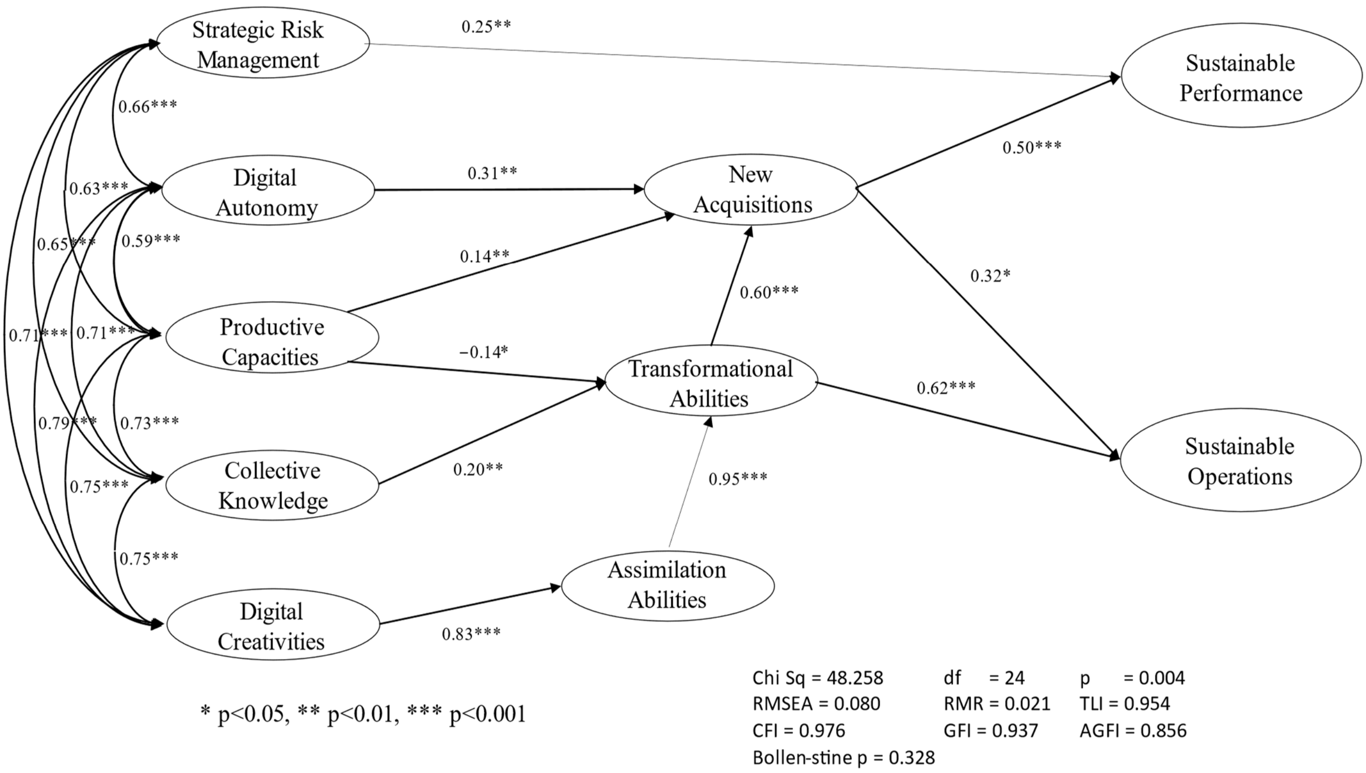

Figure 4. Software developers' three-stage SEM path model solution to ongoing sustainability.

These Table 2 single indicator constructs can be applied within the literature-developed causal framework model. Here, each construct's single indicator item is set against a 1.0 measurement error variance (set against the study's literature developed survey items focus as assessment of indicator methodology), and against this focal construct's causal connections to other model constructs whilst assuring literature supported causal appropriateness of constructs connected to multiple indicators is suitably captured [43–45].

This study notes measurement and theory remain closely related, yet the environs are set in an imperfect knowing situation but kept within literature trustworthy guidelines. This brings a close coordination between the study's literature and its resultant framework modelling. The study also places a close understanding of the modelling with the data capture, also supporting logical and causal model outcomes, and with each construct and its indicator items, together supporting and contributing towards theory and model precision [41,46].

We also model as Figure 5, the Figure 4 solution, this time complete with full independent construct items complete with their interaction effects, and again deliver a strong structural model. We conclude the Figures 4 and 5 modelling is stable and representative of the survey's software 'expert' data capture.

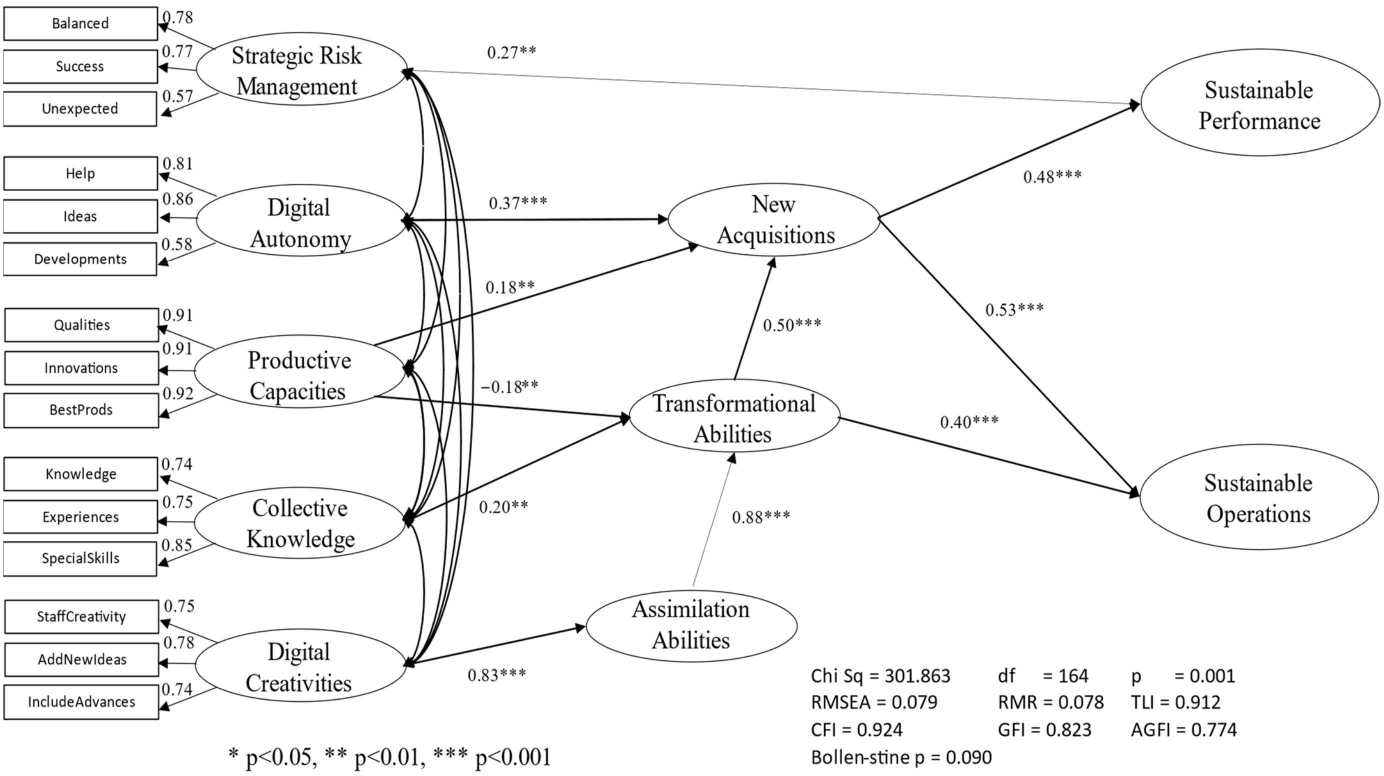

Figure 5. Software developers' three-stage SEM path model to ongoing sustainability (modelled to capture the full suite of independent construct items along with their interaction effects).

To further validate the model structure, we add the Bollen-Stine bootstrap *p* value of 0.328 for Figure 4. This shows the model fits better in 135 of 200 bootstrap samples and worse in only 65 bootstrap samples. Similarly, Figure 5's Bollen-Stine bootstrap *p* value of 0.090 fits better in 183 of 200 bootstrap samples and worse in only 17 bootstrap samples.

4.3. SEM of Table 2's Software Developer Responses

Figure 4 shows software developers perceive their deliverance of sustainable AI software development processes as a three-stage solution, commencing with an independent suite of possessed competencies. These can help build an intermediate dependent stage-two suite of developing capabilities. The independent competencies and intermediate dependent capabilities then coalesce as a solution set that helps deliver improvements to stage three's dependent ongoing sustainable performance and a sustainable operational position.

All Figure 4 paths are significant (at better than $p < 0.05$), all constructs network and interplay. A high-quality model fit is achieved (refer model fit data provided immediately below Figure 4), and all measures, except RMSEA (which offers only acceptable fit), indicate an excellent fit [29,43]. Figure 5, with its interaction effects between dependent constructs included, follows an identical but somewhat weaker path model structure. In both models, the productive capacities to new acquisitions beta path weights are positive (0.14 and 0.18), whereas the productive capacities to transformational abilities beta path weights are negative (−0.14 and −0.18). This difference is logical because productive capacities introduce available best, quality, and innovative consumer items. These likely have some influence on new acquisitions—hence a positive relationship, whereas productive capacities likely do not require additional extensive transformational abilities, hence a negative relationship. Both models display logical causal progressions. All remaining model beta pathways are both positive and significant (at better than $p < 0.01$ levels), with new acquisitions and transformational abilities actions generating moderately strong changes influences onto sustainable performance and sustainable operations outcomes.

The Figures 4 and 5 single indicator constructs can be applied within the literature-developed framework (full causal) model. Here, each construct's single indicator item is set to a 1.0 measurement error variance-set against the study's literature-developed survey items focus (the assessment of indicator methodology), and against this focal construct's causal connections to the other constructs in the model whilst also assuring the literature supported causal appropriateness of the constructs connected to multiple indicators is also captured [43–45].

Figure 4 has all independent constructs with significant covariances ($p < 0.001$) between 0.43 and 0.79 and all correlations between 0.43 and 0.79. This study notes measurement and theory remain closely related, yet the environs are set in an imperfect knowing situation but kept within literature trustworthy guidelines. This brings a close coordination between the study's literature and its resultant framework modelling. The study also places a close understanding of the modelling, with the data capture also supporting logical and causal model outcomes and with the construct and its indicator items together supporting and contributing towards theory and model precision [45,46].

5. Discussion

Today, *dynamic warehousing* is a digital intelligences, and real-time demand-process optimization solution, and *smart dynamic warehousing* incorporates integrated, automated, and, where possible, autonomous robotic 3D active machinery to operate without human workforce participation and to immediately provide and deliver consumer demanded items in near real-time. This is the direction towards which Amazon, Rio Tinto, My Chemist/Chemist Warehouse Group, and Walmart are each heading—but from different current positions! This progression often requires assistance of external software developer firms.

To assess software developer firm capabilities, Figure 4's path model can be applied. Here, the standardized total effects can be stage-grouped, and displayed in 3D, as competencies (X axis), capabilities (Y axis) and sustainability outcomes (Z axis)—with the size of each software developer firm's 'box' capturing the relative strength of each model's deliverables.

Figure 4 presents a three-stage model (competencies-to-capabilities-to-sustainability outcomes). Of the three stage-two Figure 4 intermediate capabilities constructs, only transformational abilities and new acquisitions directly and significantly affect the stage-three outcomes constructs. This suggests software developer firms can best focus on actioning and developing strong transformational abilities, plus building broad-reaching abilities that source and action new acquisitions as another part of their suite of ongoing actioning capabilities.

Hence, based on the above Figure 4 modelling solution, Amazon and also other warehousing firms can look towards partnering with software developer firms who (1) possess high competencies in strategic risk management and/or (2) allow staff a high degree of digital autonomy and/or (3) possess a high degree of proactive capacities and/or (4) continually acquire significant and relevant collective knowledge and/or (5) encourage staff to show high degrees of digital creativity. Amazon's best software development partnering is most likely where chosen software developer firms positively possess high levels of all five of these competencies and where the chosen software developer firms remain focused on developing their transformational abilities and capably optimizing latest new capabilities acquisitions.

For example, considering Amazon's ongoing target towards smart, dynamic warehousing, where (1) drones can monitor stored items or parcels, (2) shelving can move to accommodate differing parcel sizes, (3) robots can, as required, place and/or pick parcels in-and-out of storage, and (4) laser guided semi-autonomous robots can move any one-off selected items to logistical conveyors for placement, inclusion, delivery-labelling, packaging, and consumer-demanded shipping. Advancements in this real-time changeable domain likely require ongoing AI improvements—continually driven by both internal software development solutions and external partnering software developer firms' solutions. These relative, real-time generative AI system solutions likely target adding to a net-positive sustainability growth, but they can also be set to deliver a net-static sustainability status or even to a specific net-negative sustainability position.

For example, the earlier described generation 1–to–4 AI systems are today progressively being integrated into 3D, digitally twinned, remote warehouse management systems, and these networks can further software-link and allow near-warehouse, AI-supported, precise drone-specific order fulfillment delivery to specific individual consumers.

Further ongoing developments to such smart dynamic warehousing systems likely requires software developer staff who possess (1) sound strategic risk management competencies, plus (2) high degree of digital autonomy, plus (3) proactive capacities, plus (4) digitally creative competencies, plus (5) skills to collectively contribute into growing body of competitive new knowledge. This competencies suite can be particularly useful if it is actioned towards appropriately chosen deliverable capabilities.

Both software developer firms and Amazon share the need (1) to dynamically develop their capabilities into chosen new assimilation pathways, (2) to transform an existing position into something new, and (3) to acquire further areas of precise, agile capabilities deliverance. Thus, Amazon can likely consider the intermediate capabilities stages of Figure 4 when pursuing software changes or when establishing selection criteria that may help evaluate the potential of additional or new software developer firms. For example, software development companies like Altium have competencies and capabilities-linked design, manufacturing, and supply applications aspects into one sustainable solution.

Although Amazon is used as this study's primary example of software developer firm ongoing requirements, similar situations likely apply to the study's other warehousing examples (Rio Tinto, My Chemist/Chemist Warehouse Group, Walmart), and to many other substantive leading-edge AI engaging firms.

6. Conclusions

This study advances knowledge in the AI field. It provides deep insight into current industry generative AI inclusion systems. It shows both literature and practical leading industry operations can link, overlap, and complement each other when it comes to AI and its processing complexities. It shows how to model and link AI inclusions towards a sustainability positioning. It shows how to integrate external AI contributions from one firm into another firm's suite of intelligences developments. It shows how to track, and maybe benchmark, the progress of such AI inclusions from either an external or an integrated internal software developer perspective. It shows how to understand and create a more sustainable, AI integrated business positioning.

This study offers a unique perspective through which substantive firms already using AI can now model and track the relevance of their prospective or existing external software developer firms and so create rapid internal net AI incorporation, development, and sustainable solutions.

This study considers warehousing and generative AI deployment as a pathway towards smart ever-developing generative AI systems and towards inclusion into smart dynamic warehouse-of-the-future solutions. The exemplar Amazon is enlisted to focus on digital and generative AI prowess. Amazon's leading-edge warehouses are progressively offering further smart dynamic warehousing solutions into their business model. This likely necessitates the inclusion of complex internal software development, coupled with the inclusion of relevant and specifically selected external software developer firms. Such software developer firms likely consistently attune themselves towards even higher performing, sustainable, AI focused entities, and/or towards being higher operationally productive AI enabling sustainable entities.

This study shows Amazon, and likely other leading-edge warehousing operations, can specifically select the external software developer firms that likely best help improve their chosen generative AI advancements. The SEM pathways model of leading-edge software developer firms in Pakistan suggests a three-stage software developer firm process exists and that constructs presented herein offer warehouse pathways that can be applied when choosing relevant AI competencies and AI capabilities—particularly ones that likely include latest relevant generative AI systems. These may be associated with relevant automation, AI enhanced robotics, and/or efficient logistics responses. Warehouse operators can frame these generative AI systems towards helping them assess and track software capabilities developments and to further map them against changes in both operational and performance sustainability outcomes.

7. Limitations

The total effects of the competencies and capabilities constructs on the two outcome-dependent variables suggests further considerations can be included when determining and selecting further appropriate external software developer firm item contributions for inclusion in warehousing and its generative AI developments. However, this study's constructs provide a solid starting point. Considering competencies, digital creativity (68%), collective knowledge (24%), and digital autonomy (10%) deliver strongest significant influences onto sustainable operations, whilst digital creativity (26%), strategic risk management (25%), and digital autonomy (15%) deliver strongest significant influences on sustainable performance. Further, considering capabilities, assimilation abilities (81%) and transformational abilities (81%) deliver strong influences on sustainable operations and around 30% influences on sustainable performance, whilst new acquisitions exert around a 30% influence on sustainable operations and a 50% influence on sustainable performance.

Thus, others can likely use this three-stage SEM approach to software development and can expand this research model by engaging additional, specifically relevant (and significant) warehouse-related construct item measures.

Author Contributions: J.R.H. developed and wrote this paper. S.A.A. conducted the survey, collated data, and helped perform data analysis. S.T. helped develop the survey and perform data analysis. Further details: paper conceptualization, J.R.H., S.J.M., S.A.A. and S.T.; methodology, J.R.H.; software, J.R.H., S.A.A. and S.T.; validation, J.R.H., S.A.A. and S.T.; formal analysis, J.R.H., S.A.A. and S.T.; investigation, J.R.H., S.J.M., S.A.A. and S.T.; resources, J.R.H. and S.A.A.; data curation, J.R.H., S.A.A. and S.T.; writing—original draft preparation, J.R.H. and S.J.M.; writing—review and editing, J.R.H., S.J.M., S.A.A. and S.T.; visualization, J.R.H.; supervision, J.R.H. and S.T. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Research data to be made available via Research Data JCU via the following link https://www.jcu.edu.au/rdim/research-data-jcu-platform (accessed on 28 March 2024).

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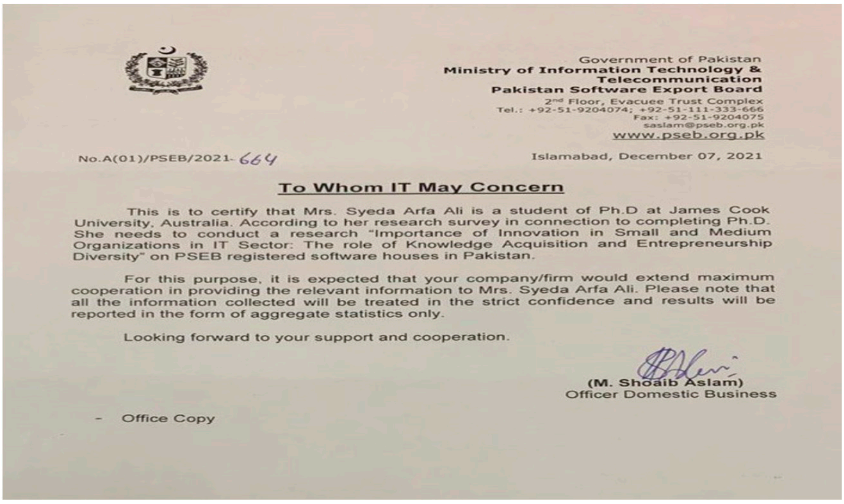
Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Formal Government of Pakistan Access and Support Document



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No.A(01)/PSEB/2021-664

Islamabad, December 07, 2021

To Whom IT May Concern

This is to certify that Mrs. Syeda Arfa Ali is a student of Ph.D at James Cook University, Australia. According to her research survey in connection to completing Ph.D. She needs to conduct a research "Importance of Innovation in Small and Medium Organizations in IT Sector: The role of Knowledge Acquisition and Entrepreneurship Diversity" on PSEB registered software houses in Pakistan.

For this purpose, it is expected that your company/firm would extend maximum cooperation in providing the relevant information to Mrs. Syeda Arfa Ali. Please note that all the information collected will be treated in the strict confidence and results will be reported in the form of aggregate statistics only.

Looking forward to your support and cooperation.

(M. Shoaib Aslam)
Officer Domestic Business

- Office Copy

References

1. Copeland, B.J. Artificial Intelligence. *Britannica*. 3 February 2024. Available online: https://www.britannica.com/technology/artificial-intelligence (accessed on 6 February 2024).
2. Cowell, A. Overlooked No More: Alan Turing, Condemned Code Breaker and Computer Visionary. *New York Times*. 5 June 2019. Available online: https://www.nytimes.com/2019/06/05/obituaries/alan-turing-overlooked.html (accessed on 6 February 2024).
3. Chen, Z.; Wu, M.; Chan, A.; Li, X.; Ong, Y.S. Survey on ai sustainability: Emerging trends on learning algorithms and research challenges. *IEEE Comput. Intell. Mag.* **2023**, *18*, 60–77. [CrossRef]
4. Rakha, N.A. Artificial Intelligence and Sustainability. *Int. J. Cyber Law* **2023**, *1*, 1–12.
5. van Wynsberghe, A.; Vandemeulebroucke, T.; Bolte, L.; Nachid, J. Special Issue "Towards the Sustainability of AI; Multi-Disciplinary Approaches to Investigate the Hidden Costs of AI". *Sustainability* **2022**, *14*, 16352. [CrossRef]
6. Kindylidi, I.; Cabral, T.S. Sustainability of AI: The case of provision of information to consumers. *Sustainability* **2021**, *13*, 12064. [CrossRef]
7. Weng, J.; Evans, C.; Hwang, W.S.; Lee, Y.B. The developmental approach to artificial intelligence: Concepts, developmental algorithms and experimental results. In Proceedings of the NSF Design and Manufacturing Grantees Conference, Long Beach, CA, USA, 5–8 January 1999; Michigan State University: East Lansing, MI, USA, 1999; pp. 1–33.
8. Dawson, C.W.; Dawson, R.J. An artificial intelligence approach to software development management and planning. *WIT Trans. Inf. Commun. Technol.* **1970**, *2*, 135–150.
9. Hamilton, J.R.; Maxwell, S.J.; Tee, S. AI and Firm Competitiveness. In Proceedings of the 23rd International Conference on Electronic Business, ICEB'23, Chiayi, Taiwan, 17–23 October 2023; Volume 23, pp. 17–24.
10. Hamilton, J.R.; Maxwell, S.J.; Lynch, R.P. Towards delivering AI & smarter, self-learning, autonomous, humanoid robots. In Proceedings of the 23rd International Conference on Electronic Business, ICEB'23, Chiayi, Taiwan, 17–23 October 2023; Volume 23, pp. 667–674.
11. Anon1 10 Stages of AI Development. Available online: https://www.youtube.com/watch?v=AK5EwG62hx8 (accessed on 2 February 2023).
12. AI TechXplorer, Unveiling the 10 Stages of AI: What You Need to Know NOW! Available online: https://www.youtube.com/watch?v=AK5EwG62hx8&t=4s (accessed on 2 February 2023).
13. Hamilton, J.R.; Maxwell, S. Artificial Intelligence (AI), Rio Tinto and Firm Leading-Edge AI Competitiveness Model. In Proceedings of the 23rd International Conference on Electronic Business, ICEB'23, Chiayi, Taiwan, 17–23 October 2023; Volume 23, pp. 36–44.
14. Hamilton, J.R. Service Value Networks and the Business-Customer Encounter. Doctoral Thesis, Macquarie University, Sydney, Australia, 2006; pp. 1–280.
15. Kumar, S.; Narkhede, B.E.; Jain, K. Revisiting the warehouse research through an evolutionary lens: A review from 1990 to 2019. *Int. J. Prod. Res.* **2021**, *59*, 3470–3492. [CrossRef]
16. Pontius, N. The Complete Guide to Warehouse Automation: Basics of Organization and Warehouse Labeling, Automation Technologies, Best Practices, and More. Camcode: Industry Resources, Warehouse Labels, Updated November 23, 2023. Available online: https://www.camcode.com/asset-tags/guide-to-warehouse-automation/ (accessed on 10 February 2024).

17. Buerkle, A.; Eaton, W.; Al-Yacoub, A.; Zimmer, M.; Kinnell, P.; Henshaw, M.; Coombes, M.; Chen, W.-H.; Lohse, N. Towards industrial robots as a service (IRaaS): Flexibility, usability, safety and business models. *Robot. Comput.-Integr. Manuf.* **2023**, *81*, 102484. [CrossRef]
18. Mahmud, P.; Paul, S.K.; Azeem, A.; Chowdhury, P. Evaluating supply chain collaboration barriers in small- and medium-sized enterprises. *Sustainability* **2021**, *13*, 7449. [CrossRef]
19. Kumar, A.; Liu, R.; Shan, Z. Is blockchain a silver bullet for supply chain management? Technical challenges and research opportunities. *Decis. Sci.* **2020**, *51*, 8–37. [CrossRef]
20. Ahmadi, S. Optimizing Data Warehousing Performance through Machine Learning Algorithms in the Cloud. *Int. J. Sci. Res.* **2023**, *12*, 1859–1867.
21. Conrad, L. Amazon's AI logistics Warehouses. 30 December 2021. Available online: https://tbtech.co/featured-news/amazons-ai-logistics-warehouses/ (accessed on 24 February 2023).
22. Lindsay, A. How AI and Analytics Are Transforming Procurement. Amazon Business. 2020. Available online: https://business.amazon.com/en/discover-more/blog/how-ai-and-ml-are-transforming-procurement (accessed on 3 February 2024).
23. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Messner, D.; Nakicenovic, N.; Rockström, J. Six transformations to achieve the sustainable development goals. *Nat. Sustain.* **2019**, *2*, 805–814. [CrossRef]
24. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. [CrossRef]
25. Bag, S.; Pretorius, J.H.C.; Gupta, S.; Dwivedi, Y.K. Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technol. Forecast. Soc. Chang.* **2021**, *163*, 120420. [CrossRef]
26. Katsamakas, E. From Digital to AI Transformation for Sustainability. *Sustainability* **2024**, *16*, 3293. [CrossRef]
27. Rajput, S.; Singh, S.P. Industry 4.0 Model for circular economy and cleaner production. *J. Clean. Prod.* **2020**, *2020*, 123853. [CrossRef]
28. Aziz, S.; Dowling, M. Machine learning and AI for risk management. In *Disrupting Finance: FinTech and Strategy in the 21st Century*; Lynn, T., Mooney, J.G., Rosati, P., Cummins, M., Eds.; Palgrave McMillan: Cham, Switzerland, 2019; pp. 33–50.
29. Shah, H.M.; Gardas, B.B.; Narwane, V.S.; Mehta, H.S. The contemporary state of big data analytics and artificial intelligence towards intelligent supply chain risk management: A comprehensive review. *Kybernetes* **2023**, *52*, 1643–1697. [CrossRef]
30. Schuett, J. Risk management in the artificial intelligence act. *Eur. J. Risk Regul.* **2023**, *14*, 1–19. [CrossRef]
31. Richey, R.G., Jr.; Chowdhury, S.; Davis-Sramek, B.; Giannakis, M.; Dwivedi, Y.K. Artificial intelligence in logistics and supply chain management: A primer and roadmap for research. *J. Bus. Logist.* **2023**, *44*, 532–549. [CrossRef]
32. Rathor, K. Impact of using Artificial Intelligence-Based ChatGPT Technology for Achieving Sustainable Supply Chain Management Practices in Selected Industries. *Int. J. Comput. Trends Technol.* **2023**, *71*, 34–40. [CrossRef]
33. Weber, M.; Engert, M.; Schaffer, N.; Weking, J.; Krcmar, H. Organizational capabilities for AI implementation—Coping with inscrutability and data dependency in AI. *Inf. Syst. Front.* **2023**, *25*, 1549–1569. [CrossRef]
34. Huu, P.T. Impact of employee digital competence on the relationship between digital autonomy and innovative work behavior: A systematic review. *Artif. Intell. Rev.* **2023**, *56*, 14193–14222. [CrossRef]
35. Mikalef, P.; Gupta, M. Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Inf. Manag.* **2021**, *58*, 103434. [CrossRef]
36. Budhwar, P.; Chowdhury, S.; Wood, G.; Aguinis, H.; Bamber, G.J.; Beltran, J.R.; Boselie, P.; Cooke, F.L.; Decker, S.; DeNisi, A.; et al. Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Hum. Resour. Manag. J.* **2023**, *33*, 606–659. [CrossRef]
37. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Artificial intelligence applications for industry 4.0: A literature-based study. *J. Ind. Integr. Manag.* **2022**, *7*, 83–111. [CrossRef]
38. Jacobides, M.G.; Brusoni, S.; Candelon, F. The evolutionary dynamics of the artificial intelligence ecosystem. *Strategy Sci.* **2021**, *6*, 412–435. [CrossRef]
39. Abrardi, L.; Cambini, C.; Rondi, L. Artificial intelligence, firms and consumer behavior: A survey. *J. Econ. Surv.* **2022**, *36*, 969–991. [CrossRef]
40. Zekos, G.I. Digital Economy Competition. In *Artificial Intelligence and Competition. Contributions to Economics*; Georgious, I.Z., Ed.; Springer: Cham, Switzerland, 2023.
41. Papa, A.; Santoro, G.; Tirabeni, L.; Monge, F. Social media as tool for facilitating knowledge creation and innovation in small and medium enterprises. *Balt. J. Manag.* **2018**, *13*, 329–344. [CrossRef]
42. Alshanty, A.M.; Emeagwali, O.L. Market-sensing capability, knowledge creation and innovation: The moderating role of entrepreneurial-orientation. *J. Innov. Knowl.* **2019**, *4*, 171–178. [CrossRef]
43. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L. *Multivariate Data Analysis*, 7th ed.; Pearson: Upper Saddle River, NJ, USA, 2014.
44. Munck, I. *Model Building in Comparative Education: Applications of LISREL Method to Cross-National Survey*; Almqvist & Wiksell International: Stockholm, Sweden, 1979; pp. 1–199.

45. Cunningham, E. *A Practical Guide to Structure Equation Modeling Using AMOS*; Streams, Statsline: Melbourne, Australia, 2008.
46. Hayduk, L.A.; Littvay, L. Should researchers use single indicators, best indicators, or multiple indicators in structural equation models? *BMC Med. Res. Methodol.* **2012**, *12*, 159. Available online: http://www.biomedcentral.com/1471-2288/12/159 (accessed on 1 February 2024). [CrossRef]