

Ecosystem Drivers of Digital Spare Parts Adoption: Evidence from an SEM Study in UAE Industries

Wadhah Alzahmi

Department of Industrial Engineering, American University of Sharjah, Sharjah, United Arab Emirates
Email: g00093682@aus.edu

Abdulrahim Shamayleh

Department of Industrial Engineering, American University of Sharjah, Sharjah, United Arab Emirates
Email: ashamayleh@aus.edu

ABSTRACT

Spare parts management is a persistent operational challenge, often constrained by long lead times, high inventory costs, and frequent supply chain disruptions. Digital spare parts (DSP), enabled by additive manufacturing and digital technologies, provide a promising alternative through localized production and demand-driven supply. Yet, successful DSP adoption requires more than technological readiness; it depends on a systemic understanding of the ecosystem of enablers that shape both economic and operational viability. This study develops and empirically validates a structural model of DSP ecosystem readiness in the United Arab Emirates, an emerging economy pursuing industrial diversification. Data were collected from 162 industry professionals across energy, manufacturing, healthcare, automotive, and aerospace sectors. Using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM), the study examines the interdependencies among 13 critical ecosystem factors. Findings show that infrastructure readiness, cost management, vendor support, customization capability, and quality assurance significantly and positively influence DSP adoption. In contrast, material availability, scalability, and industry readiness demonstrate counterintuitive negative effects, while sustainability and risk management exhibit no significant direct impacts. The results highlight the complex interplay of economic and operational drivers, providing an empirically grounded framework for understanding DSP ecosystem readiness and offering analytical insights for researchers and industry practitioners.

Keywords: Digital Spare Parts (DSP); Additive Manufacturing; Structural Equation Modeling (SEM); Industry 4.0; Technological Adoption; Factor Analysis

1. INTRODUCTION

Spare parts management represents one of the most persistent operational and economic challenges in industrial systems. Downtime due to unavailable components directly translates into production losses, excess safety stock inflates inventory costs, and global supply chain disruptions amplify

uncertainty. Addressing these inefficiencies requires more than incremental improvements; it calls for new approaches to sourcing, production, and logistics. Digitization of spare parts, commonly referred to as Digital Spare Parts (DSP), has emerged as a transformative innovation in modern industrial systems. Leveraging advancements in additive manufacturing (AM), digital inventory management, and cloud-enabled distribution platforms, DSP enables organizations to reduce lead times, lower inventory costs, and respond to real-time demand with greater agility. These advantages are particularly significant for high-dependency industries such as aerospace, energy, automotive, and healthcare, where equipment downtime directly translates into financial and operational risks (Peron, 2024; Tziantopoulos *et al.*, 2016).

Despite growing interest and investment, the widespread adoption of DSP technologies remains inconsistent and fragmented. One of the main barriers lies in the misconception that adoption success depends solely on the presence of individual technological enablers. In reality, DSP implementation is shaped by a complex ecosystem of interdependent factors that span technological capabilities, operational infrastructure, vendor support, regulatory compliance, cost structures, and strategic alignment. These factors do not operate in isolation; instead, they often interact reinforcing or constraining each other (Chekurov *et al.*, 2021). As a result, organizations face uncertainty about where to allocate resources and which enablers to prioritize.

Recent research on the readiness of DSP and AM increasingly critiques traditional studies for focusing on individual factors in isolation, which often leads to only partial explanations of readiness outcomes. For example, Holmström *et al.* (2010) argue that the impact of AM on spare parts supply chains cannot be understood by examining isolated factors, but instead requires an integrated, systems-level perspective that considers the entire supply chain ecosystem. Similarly, Pantelidakis *et al.* (2022) highlight that most previous research on AM focuses on individual process components, whereas their work demonstrates the value of a digital twin ecosystem for managing and optimizing AM as a whole system. González-Varona *et al.* (2020) further note that while much of the literature has concentrated on large companies and single factors, there is a growing need for

integrative, ecosystem-based frameworks to support AM adoption, particularly for small and medium-sized enterprises. Additionally, Bade et al. (2025) use a systems-level approach to analyze how Industry 4.0 technologies, including AM, are transforming the automotive spare parts supply chain, emphasizing the importance of understanding the interplay between technology, supply chain structure, and business models. Collectively, these studies underscore a clear and growing call within the academic literature to move beyond fragmented, single-factor analyses and adopt integrative, ecosystem-based frameworks that better capture the complexities of DSP and AM adoption.

This study responds to that call by applying Structural Equation Modeling (SEM) to empirically test the interdependencies among critical enablers of DSP ecosystem adoption. SEM is particularly suitable as it enables simultaneous analysis of multiple latent constructs and their interrelationships, offering insights into how ecosystem readiness is collectively shaped.

The United Arab Emirates (UAE) provides a relevant empirical setting for this investigation due to its proactive national strategies, such as Operation 300bn and the Dubai 3D Printing Strategy, which aim to position the country as a global hub for advanced manufacturing. However, the unique industrial maturity, regulatory structure, and supply chain configuration in the UAE highlight the importance of empirically examining DSP ecosystem readiness within this emerging industrial context (Aljarwan et al., 2019; Bahloolq et al., 2020).

To address this gap, the study identifies 13 ecosystem enablers through a systematic literature review. These factors were then translated into 39 measurable indicators designed to capture ecosystem dynamics with both academic rigor and contextual specificity. A nationwide survey targeting professionals across critical sectors, including energy, healthcare, aerospace, automotive, and manufacturing, was conducted to gather the data necessary for rigorous validation and interrelationship modeling.

The core objective of this study is to develop and empirically validate a structural model that reveals how key ecosystem factors interact and collectively influence DSP adoption readiness. Specifically, the study aims to:

- Quantify the strength and direction of influence of each factor on overall readiness;
- Explore systemic interdependencies among the factors;
- Identify high-impact leverage points where strategic interventions could accelerate DSP adoption.

By moving beyond factor-based analysis to model systemic relationships, this research contributes both theoretically and practically. It offers a validated, context-specific framework that enriches academic discourse on digital manufacturing ecosystems and provides policymakers and industry leaders with actionable insights for strategic planning, infrastructure investment, and policy formulation.

In doing so, the study reinforces the idea that successful DSP readiness is not merely a function of technological availability but the outcome of a well-orchestrated ecosystem where interrelated enablers function in harmony. The resulting model serves as both a diagnostic tool for assessing readiness and a strategic guide for aligning national objectives with enterprise-level transformation efforts.

2. LITERATURE REVIEW

Readiness for DSP adoption reflects not only technological availability but the alignment of economic, operational, and institutional enablers that determine cost-effectiveness, scalability, and supply chain resilience. As prior literature has demonstrated, technology implementation alone is not a sufficient predictor of readiness; rather, it is the combined influence of technological, operational, and institutional enablers that determines scalability and impact across industries. Studies in the domains of industrial engineering, innovation management, and digital transformation consistently emphasize that isolated examination of readiness drivers offers limited explanatory power and fails to reflect the systemic dependencies required for implementation (Frank et al., 2019; Holmström et al., 2010; Kiel et al., 2017). This underscores the need to move beyond firm-level analyses and instead examine the broader ecosystem conditions that enable or constrain the integration of DSP.

Enablers within a digital ecosystem are not merely supportive elements; they are structural determinants that govern the viability, pace, and scalability of adoption (Kiel et al., 2017). In the case of DSP, these enablers form the conditions under which additive manufacturing technologies can transition from isolated applications to embedded industrial capabilities (Holmström et al., 2010). They reflect the maturity of surrounding systems, technical standards, infrastructure alignment, regulatory preparedness, supplier ecosystems, and institutional engagement that collectively frame the operational reality of DSP implementation (Pereira & Romero, 2017). When aligned, these conditions create a foundation for efficient, compliant, and responsive spare parts production. When absent or underdeveloped, they expose the ecosystem to fragmentation, inefficiency, or systemic inertia (Dalenogare et al., 2018). This perspective aligns with the broader transformation occurring in operations and supply chain management, where traditional production boundaries are increasingly reshaped through Industry 4.0 technologies, Internet of Things (IoT) connectivity, integrated information networks, and digitally enabled service delivery models (Yalcin et al., 2020). The following sections examine these enablers and establish the theoretical foundations for the study's structural hypotheses.

2.1 Technological Compatibility

Advancements in 3D printing hardware have played a pivotal role in enhancing the industrial viability of DSP through improvements in functionality, precision, and process integration. One critical indicator is Multi-Process Integration Capability, which reflects the ability of hardware systems to support hybrid and multi-material manufacturing. Researchers have explored techniques such as Multi-Material Additive Manufacturing (MMAM), including vat photopolymerization, direct ink writing, and binder jetting (Han & Lee, 2020) as well as hybrid methods that combine additive and subtractive processes to produce complex, multifunctional components with higher dimensional accuracy (Rabalo et al., 2023).

The second indicator, Smart Automation and Real-Time Monitoring, captures the role of embedded automation in enhancing efficiency and reducing manual intervention. Key developments include robotic integration, automated part removal systems, and the application of AI, IoT, and

PLC-based technologies for real-time sensing, process optimization, and predictive maintenance (Tamir *et al.*, 2023). These features enable intelligent decision-making during the printing process and reduce downtime through proactive fault detection.

Finally, Precision and Feedback Control Mechanisms represent the third indicator and are essential for maintaining part quality and reliability. Enhancements in extrusion systems, print-head dynamics, and layer monitoring have significantly improved resolution and repeatability. Researchers have introduced displacement mechanisms such as Cartesian, delta, and polar systems to improve surface finish (Quigley *et al.*, 2023), alongside thermal management solutions like enclosed chambers and heated beds to mitigate warping and improve material behavior (Snapp *et al.*, 2021). The integration of in-process sensors has further enabled real-time feedback loops for error correction and deposition control (Trejo-Morales *et al.*, 2024).

Taken together, these studies indicate that technological compatibility depends on the integration of hardware capabilities, intelligent automation, and precision control mechanisms. However, existing research presents these dimensions as independently advancing enablers, with limited examination of how their interaction shapes system-level performance. For example, while advancements in automation improve process efficiency, their impact remains constrained when not aligned with precision control mechanisms or hardware adaptability. As a result, technological compatibility should be evaluated as an integrated system-level capability within the DSP ecosystem. While previous studies have examined individual technological capabilities, limited research has assessed their collective influence on DSP ecosystem readiness. Given that interoperability, automation, and process integration support more efficient implementation and operation, higher levels of technological compatibility are expected to positively influence DSP ecosystem readiness.

Hypothesis 1 (H1): Technological Compatibility has a positive impact on shaping a successful DSP ecosystem.

2.2 Material Availability & Performance

Recent advancements in material science are central to advancing DSP readiness through AM. The first key enabler, Availability of Materials, reflects the growing diversity and accessibility of AM-compatible substances. Researchers have expanded the use of polymers, composites, metals, biodegradable bioplastics, and smart materials such as shape memory polymers and hydrogels (Tetsuka & Shin, 2020). Metal AM applications in aerospace and medical sectors continue to evolve, addressing speed, weight reduction, and design complexity (Das *et al.*, 2016). At the same time, research in biodegradable alternatives and recycled polymers supports sustainability goals while also expanding the usable material range (Olawumi *et al.*, 2023).

The second indicator, Compatibility of Materials with Operational Conditions, involves efforts to ensure that materials used in AM processes meet specific performance standards under various functional environments. Studies have focused on improving mechanical properties such as tensile strength, impact resistance, and flexibility as well as thermal behavior, fatigue life, and biocompatibility (Amini & Chang, 2018; V. V. P. Babu & Vinod Kumar, 2022).

Fiber-reinforced composites, for instance, have demonstrated exceptional strength-to-weight ratios for automotive and aerospace components (Tuli *et al.*, 2024). In 4D printing, the ability of smart materials to adapt to stimuli introduces potential in healthcare and robotics (Kantaros *et al.*, 2023).

Finally, Consistency in Local Access and Certification of Validated Materials is a critical enabler for ecosystem scalability. Despite material innovations, the lack of harmonized standards and limited regional validation infrastructure often slow industrial uptake. Researchers have proposed distributed recycling frameworks and national certification protocols to address material traceability, quality assurance, and compliance (Kassab *et al.*, 2023), (Al Rashid & Koç, 2023). Advanced characterization methods such as X-ray tomography, mechanical testing, and thermal analysis are increasingly used to ensure consistency in production and performance (Ferreira *et al.*, 2019; Meurer & Classen, 2021).

While existing studies highlight advancements in material diversity, performance, and certification practices, limited research has examined how these material-related factors collectively influence DSP ecosystem readiness. For instance, increased material availability is often associated with improved adoption potential; however, in the absence of standardized certification frameworks and validation infrastructure, it may instead introduce uncertainty regarding reliability and compliance. Most studies focus on material development and validation in specific applications, providing limited empirical evidence regarding their contribution to ecosystem-level adoption. Given that access to reliable, high-performing, and validated materials is a fundamental requirement for additive manufacturing implementation, higher levels of material availability and performance are expected to positively influence DSP ecosystem readiness.

Hypothesis 2 (H2): Material Availability & Performance has a positive impact on shaping a successful DSP ecosystem.

2.3 Infrastructure Requirements

Infrastructure requirements are a critical enabler for the successful readiness of AM in DSP. These requirements go beyond physical assets, encompassing the digital and operational systems that support seamless data exchange, platform compatibility, and end-to-end production continuity. First, data interoperability readiness is vital due to the complex and voluminous datasets generated during AM processes. Without standardized formats and integration protocols, interoperability issues can lead to inefficiencies, conversion errors, and data loss (Perišić *et al.*, 2021; Perišić *et al.*, 2022). Emerging frameworks such as STEP-NC, AutomationML, and blockchain-based data platforms aim to address these gaps by enabling real-time data synchronization, security, and traceability across digital platforms (Bonnard *et al.*, 2018).

Second, software-hardware compatibility presents a persistent barrier, especially as AM technologies depend on specialized slicing, simulation, and optimization tools that often do not integrate natively with legacy CAD/CAM, ERP, or MES systems (Mhapsekar *et al.*, 2018; Prathyusha & Babu, 2022). To bridge this disconnect, researchers have

proposed hybrid architectures, unified CAD/CAPP/ERP environments, and cloud-based manufacturing execution systems (Kim *et al.*, 2015). This digital thread integration mirrors the broader operations paradigm where advanced analytical data exchanges and cloud multi-echelon architectures act as systemic game-changers that directly elevate overall operational agility and firm capability (Darbanian *et al.*, 2024). These solutions aim to enhance semantic alignment, ensure robust communication between equipment and software layers, and support scalability (Kutin *et al.*, 2018).

Third, workflow integration capability is essential for harmonizing AM's flexible and iterative production style with traditional manufacturing's linear workflows. AM often requires post-processing, customized scheduling, and real-time monitoring of factors that can create bottlenecks if not adequately managed (Bourell *et al.*, 2020; Moehring *et al.*, 2023). As a result, infrastructure strategies now incorporate sensor-enabled monitoring, AI-based defect detection, and adaptive scheduling systems to enable a smoother flow of materials, data, and decisions (AbouelNour & Gupta, 2022).

Collectively, these studies demonstrate that infrastructure readiness depends on the alignment of data interoperability, software–hardware compatibility, and workflow integration. However, the literature presents these dimensions as independently evolving capabilities, with limited examination of how their interaction shapes system-level performance. For instance, while advances in data interoperability improve information exchange, their impact remains constrained when software–hardware compatibility is insufficient or when workflow integration is not fully achieved. Similarly, efforts to enhance workflow integration may introduce bottlenecks if underlying data standards and platform compatibility are not aligned. These interdependencies indicate that infrastructure readiness cannot be achieved through isolated technological improvements alone. Effective DSP implementation instead depends on coordinated interoperability between data systems, software platforms, and operational workflows across the broader ecosystem. Therefore, higher levels of infrastructure readiness are expected to positively influence DSP ecosystem readiness.

Hypothesis 3 (H3): Infrastructure Requirements have a positive impact on shaping a successful DSP ecosystem.

2.4 Cost

Cost remains a decisive enabler for the readiness of DSP, influencing both strategic planning and operational feasibility. The first enabler, Affordability of DSP technologies, is increasingly addressed through the development of low-cost 3D printers, especially with entry-level FDM and SLA systems ranging from as low as \$200 to over \$500,000 for industrial platforms (Moldovan *et al.*, 2018), (Bell, 2014). However, cost structures remain complex and multifaceted, encompassing both fixed and variable expenditures such as equipment, material, energy, training, maintenance, and post-processing (Ajay *et al.*, 2016).

The second enabler, Cost Optimization and Lifecycle Planning Practices, has been supported by the evolution of Lifecycle-oriented models such as Total Cost of Ownership (TCO), which have emerged to provide a comprehensive financial outlook across acquisition, operation, and long-

term maintenance phases (Fauth *et al.*, 2019). These models have demonstrated applicability across multiple industries, highlighting the need for tailored cost planning that considers batch size, complexity, element volume, and production timelines (Baumers *et al.*, 2017), (Kudelski *et al.*, 2017). Recent studies show that labor remains a dominant cost component, reaching over 95% of TCO in some applications, especially in sectors requiring skilled post-processing (Gkika *et al.*, 2022).

This leads to the need for the third enabler, Alignment of Cost Models with Sector Needs, which remains underdeveloped. Despite the potential for efficiency, current models often lack sector-specific granularity, with few addressing the nuanced cost dynamics of high-compliance domains like aerospace or low-margin industries such as manufacturing. As such, future research must bridge this gap by aligning cost evaluation frameworks with the operational realities and strategic priorities of different industrial sectors (Fauth *et al.*, 2019; Gkika *et al.*, 2022). As such, tailoring cost frameworks to an industrial context is essential to ensure that AM solutions are not only technically viable but economically justified for strategic adoption.

While existing studies emphasize the importance of affordability, lifecycle cost planning, and cost modeling, their implications for DSP adoption remain context-dependent. For example, reductions in equipment costs may improve accessibility; however, high operational costs, particularly labor and post-processing, can offset these gains and limit economic viability. Similarly, lifecycle cost models such as TCO provide comprehensive financial insights, yet their effectiveness depends on their alignment with sector-specific requirements, which remains underdeveloped in current research. In high-compliance industries, cost considerations are often shaped by certification and quality assurance requirements, while in low-margin sectors, cost sensitivity may outweigh technological benefits. These variations indicate that cost is not a uniform enabler, but one whose influence depends on its interaction with operational, regulatory, and industry-specific conditions. Accordingly, the economic feasibility of DSP adoption is shaped by how cost structures interact with sector-specific operational and regulatory conditions. This context-dependency aligns with established sourcing frameworks demonstrating that operations overhauls cannot place weight solely on isolated production expenses, as single-sided cost calculations frequently mask hidden risks and infrastructure tensions across the wider supply chain network (Hilmola *et al.*, 2023). Accordingly, the economic feasibility of DSP adoption is shaped by how cost structures interact with sector-specific operational and regulatory conditions. Since affordability and lifecycle cost optimization influence investment decisions and implementation feasibility, cost is expected to positively influence DSP ecosystem readiness.

Hypothesis 4 (H4): Cost has a positive impact on shaping a successful DSP ecosystem.

2.5 Scalability

Scalability is a foundational enabler for the widespread readiness of DSP through AM, shaped by three interlinked capabilities. First, achieving flexibility of production systems requires overcoming limitations in build volume, production speed, and hardware adaptability. Solutions such as modular printing (Tiwarly *et al.*, 2021), multi-robot

cooperation (Poudel *et al.*, 2020), and robotic large-scale platforms (Klaeger & Telesh, 2020) have demonstrated potential in scaling production while preserving design complexity.

Second, integrating scalable processes into existing supply chains demands compatibility with post-processing workflows, inventory systems, and material traceability mechanisms essential for shifting toward digital warehousing and on-demand production (Cardeal *et al.*, 2022; Song & Zhang, 2020). However, challenges persist in aligning operational workflows with the customization flexibility of AM (Chandima Ratnayake *et al.*, 2019; Deradjat & Minshall, 2015).

Finally, ensuring consistency in quality across scaled operations remains difficult due to interlayer defects, anisotropic properties, and thermal distortions in larger parts (Goh *et al.*, 2024). Research is advancing process control through real-time monitoring (Kladovasilakis *et al.*, 2024), predictive analytics, and standardized protocols to ensure repeatability and part reliability at scale. Without simultaneous progress across all three dimensions, scalability efforts risk becoming fragmented and unsustainable. Therefore, a cohesive focus on flexibility, integration, and quality stability is essential to operationalize AM as a mature solution for DSP manufacturing.

The literature reveals conflicting outcomes depending on ecosystem maturity. While modular and large-scale printing solutions improve production flexibility, their effectiveness is often constrained by limitations in quality consistency and supply chain integration. In early-stage ecosystems, scaling efforts may introduce operational complexity rather than efficiency gains. This indicates that scalability must be evaluated in conjunction with supporting infrastructure and quality systems. Nevertheless, the capacity to reliably scale manufacturing volumes and integrate workflows remains a fundamental requirement for transitioning from traditional supply chains to DSP-based production models. Therefore, scalability is expected to positively influence DSP ecosystem readiness.

Hypothesis 5 (H5): Scalability has a positive impact on shaping a successful DSP ecosystem.

2.6 Quality Assurance

Ensuring quality in AM for DSP hinges on three critical enablers. First, achieving material and part consistency remains a core challenge, particularly for mission-critical sectors like aerospace and healthcare, where mechanical performance, durability, and reliability are non-negotiable (De Bruycker *et al.*, 2021; Gajewski *et al.*, 2023). Variations in material properties, thermal warping, and layer inconsistencies compromise structural performance and limit the broader readiness of AM (Turner & Gold, 2015). Addressing this, researchers have explored image analysis (Fastowicz & Okarma, 2018), standardized dimensional testing (Patil *et al.*, 2015), and parameter optimization techniques to achieve dimensional stability and surface fidelity (Akande, 2015).

Second, the adoption of real-time monitoring and defect correction technologies is essential to detect anomalies early in the print process and dynamically adjust parameters. Advanced in-situ monitoring systems using thermal imaging (Borish *et al.*, 2020). Laser profilometry, and acoustic feedback (AbouelNour & Gupta, 2022). now

allow printers to respond to underfill or delamination in real time. AI-powered control systems, including machine learning and convolutional neural networks, further enhance precision by predicting and correcting print defects based on sensor and vision data (Jin *et al.*, 2020; Razaviarab *et al.*, 2019). These technologies reduce waste and rework, which is particularly critical in high-cost, high-risk applications (Gardner *et al.*, 2019; Ratnavel *et al.*, 2022).

Third, compliance with industry-wide quality standards underpins the long-term viability of AM for spare parts. Without harmonized standards, even technically successful prints may fail certification, especially in regulated environments (Galleguillos *et al.*, 2023). While ASTM and ISO have made strides in developing relevant frameworks, progress remains fragmented and slow (Kawalkar *et al.*, 2022), non-destructive testing (NDT) methods like X-ray CT, ultrasonic testing, and profilometry (Schulenburg & Herold, 2020; Soete *et al.*, 2019) are emerging as post-process verification tools, yet their cost and throughput limitations present a bottleneck for scalable deployment (Mandache, 2019).

Hence, without synchronized advancements across these three enablers, material consistency, real-time quality control, and standard compliance, industries risk fragmented implementations that undermine reliability, repeatability, and regulatory acceptance of AM-based spare parts. A holistic quality assurance strategy that spans design, production, and post-processing phases is essential for cross-sectoral DSP adoption. While quality assurance is widely recognized as critical for AM usage, its implementation varies significantly across production stages. For example, advancements in real-time monitoring improve defect detection during manufacturing; however, without corresponding progress in certification standards and post-process validation, these improvements may not translate into regulatory acceptance. Long-term DSP reliability therefore depends on maintaining alignment between monitoring technologies, certification standards, and post-process validation practices. Standardized quality metrics and real-time defect monitoring reduce performance uncertainty and improve confidence in the reliability of digitally manufactured components, thereby supporting broader organizational adoption.

Hypothesis 6 (H6): Quality Assurance has a positive impact on shaping a successful DSP ecosystem.

2.7 Regulatory Compliance

Regulation plays a foundational role in the adoption and scalability of AM for spare parts, ensuring compliance with safety, quality, and legal frameworks across industries. One key enabler is compliance with standards and certification, which is essential for validating the performance and safety of 3D-printed components, particularly in sectors like aerospace, healthcare, and offshore energy. However, the absence of harmonized standards presents barriers to widespread implementation (Gao *et al.*, 2015). Risk-based certification frameworks and streamlined part selection processes have been proposed to accelerate industry-wide adoption (Frandsen *et al.*, 2020). Nevertheless, outdated regulatory models struggle to keep pace with AM innovations, resulting in fragmented governance over material safety, performance validation, and liability (Ballardini *et al.*, 2018). Environmental

regulations remain similarly underdeveloped, lacking effective oversight of emissions, toxicity, and material sustainability, despite growing interest in bio-based and recycled alternatives (Nyika *et al.*, 2022). Without cohesive environmental standards, the industry risks misaligning innovation with sustainability goals.

The second enabler, regulatory quality and reliability management, addresses challenges related to consistency, certification, and liability. AM introduces unique complexity in maintaining quality across different machines, batches, and operators (Budzik *et al.*, 2021; Paxton, 2023). Techniques such as process monitoring, fault detection, and closed-loop control have been recommended to improve consistency (Fang *et al.*, 2022; Tamir *et al.*, 2023), while Six Sigma principles are being applied to mitigate variability (Yang *et al.*, 2020). Despite these advances, there is a lack of comprehensive testing and validation protocols, particularly for safety-critical applications. Moreover, the disruption of traditional manufacturing chains complicates legal responsibility, making it unclear who is liable for part failures, whether it is the designer, printer, or end-user (Ballardini *et al.*, 2018; S. Li & Visscher, 2020). This legal ambiguity necessitates new frameworks for managing responsibility and IP ownership throughout the AM lifecycle.

The final enabler, conformity to international regulatory frameworks, underscores the need for globally aligned policies on trade, IP, traceability, and cross-border certification. AM is challenging traditional trade patterns, with some research suggesting it may localize manufacturing, while others expect increased global integration (Abeliansky *et al.*, 2020). However, international IP laws remain inadequate for protecting digital design files, which can be easily replicated or shared without authorization (Ballardini *et al.*, 2018). Emerging technologies, such as blockchain and digital tagging systems, are being explored to safeguard design integrity and ensure traceability (Chan *et al.*, 2023). Solutions like barcoding, blockchain-enabled validation, and "Digital Thread" informatics systems have been proposed to enhance part verification and streamline certification processes across borders (Mies *et al.*, 2016). Nevertheless, a comprehensive and unified international approach is still lacking. Without this, issues related to IP infringement, customs compliance, and global certification will continue to hinder AM's adoption.

In conclusion, regulation is a critical enabler of AM adoption, intersecting with technical, operational, and legal domains to ensure quality, safety, and compliance in spare parts production. While some sectors have begun developing certification paths and traceability protocols, the regulatory environment remains fragmented. For example, advances in certification and traceability in aerospace and healthcare contrast with limited regulatory clarity in other sectors, creating inconsistencies in implementation. In addition, the lack of alignment between environmental regulations, quality standards, and international compliance frameworks introduces uncertainty that can slow adoption. Regulatory effectiveness is therefore shaped not only by the existence of standards, but also by their consistency across industries, jurisdictions, and lifecycle stages. Transparent regulatory criteria and structured liability management reduce legal

ambiguities and implementation uncertainty, thereby providing institutional support for ecosystem integration and adoption.

Hypothesis 7 (H7): Regulatory Compliance has a positive impact on shaping a successful DSP ecosystem.

2.8 Industry Readiness

Industry readiness is fundamentally shaped by three interconnected enablers: Technological and Infrastructure Readiness, Workforce and Organizational Readiness, and Innovation Investment. From a technological and infrastructure standpoint, readiness involves not only the maturity of AM tools but also the supporting digital ecosystem and physical capabilities required for implementation. Studies have proposed various maturity and readiness models to assess digital integration and Industry 4.0 alignment in manufacturing firms (Çınar *et al.*, 2021; De Carolis *et al.*, 2017). However, technical barriers persist, including post-processing limitations, small build volumes, and the absence of robust decision-support systems for part selection and process suitability (Kretzschmar *et al.*, 2018). SMEs, in particular, face greater challenges due to constrained resources and infrastructure gaps (Pirola *et al.*, 2020). Moreover, successful AM integration relies on advanced digital infrastructure such as CAD systems, quality control software, and inventory optimization tools, which many firms lack or underutilize (Chekurov *et al.*, 2021).

From a workforce and organizational readiness perspective, a pronounced gap exists in technical and managerial capabilities to support AM deployment. Research points to the necessity for multidisciplinary education, hands-on training, and academic–industry collaboration to bridge skill deficits (Despeisse & Minshall, 2017; Mehta & Berdanier, 2019). Organizations also struggle with change resistance, poor awareness, and limited leadership engagement, all of which hinder AM adoption (Ukobitz, 2020; Waqar *et al.*, 2024). Effective implementation demands organizational alignment, including readiness for cultural transformation and structured policy support (Motzer *et al.*, 2020).

Investment in innovation is the final but critical enabler, ensuring that industries remain agile and responsive to emerging AM capabilities. Continuous investment in R&D spanning materials science, software development, and AM hardware is essential to improve system performance and meet sector-specific requirements (Kretzschmar *et al.*, 2018; Savastano *et al.*, 2016). Case studies demonstrate that collaboration among universities, companies, and technology providers can drive innovation; however, these partnerships are often fragmented and lack strategic direction (Flores Ituarte *et al.*, 2016).

Despite promising efforts, there is currently no unified framework that consolidates these readiness dimensions into a single evaluation tool. Most existing models focus narrowly on specific industries or national contexts, leaving a critical gap in cross-sectoral, scalable readiness assessments. Addressing this shortfall requires developing flexible, multi-dimensional frameworks that incorporate technical maturity, workforce preparedness, organizational capacity, and innovation strategy to guide a holistic transition toward AM in spare parts ecosystems. Industry readiness therefore emerges from the combined maturity of technological infrastructure, workforce capability,

organizational alignment, and innovation investment. Higher organizational maturity, workforce expertise, and innovation investment provide the capabilities necessary to successfully implement DSP initiatives and support ecosystem readiness.

Hypothesis 8 (H8): Industry Readiness has a positive impact on shaping a successful DSP ecosystem.

2.9 Customization Need

Customization in AM is a strategic capability that addresses diverse operational needs across industries by aligning product design, digital integration, and supply chain responsiveness. At its core, customization meets industry-specific design requirements, particularly in sectors such as aerospace, healthcare, and electronics where components often require unique geometries, material compositions, or performance features. For example, aerospace demands lightweight but durable structures (Martinez *et al.*, 2022), while healthcare necessitates biocompatible, patient-specific components (Mobarak *et al.*, 2023). AM enables rapid prototyping and iterative design, making it possible to respond to unique functional demands and equipment-specific failures quickly and efficiently (Coruzzolo *et al.*, 2022). However, realizing this potential still requires overcoming material limitations and feasibility constraints, which are ongoing areas of research (Beiderbeck *et al.*, 2018; Peron & Sgarbossa, 2021).

Beyond design, customization is significantly enhanced through the integration with digital technologies such as CAD, CAE, digital twins, and AI-based optimization systems. These tools enable the simulation, refinement, and validation of designs before production, increasing the reliability and precision of customized parts (Kantaros & Ganetsos, 2024). Techniques such as reverse engineering using 3D scanning and agile hardware development enable cost-efficient spare part replication and improvement (Montero *et al.*, 2020; Rešetar *et al.*, 2024). Furthermore, integrating AM into supply chain analytics and resource planning using AI and digital platforms supports intelligent part design, inventory control, and demand-driven manufacturing (de Brito *et al.*, 2020; Iraqi *et al.*, 2016) reinforcing AM's role in operational agility.

Finally, the impact on supply chain flexibility is a defining enabler of customization through AM. By enabling on-demand, localized production, AM significantly reduces inventory requirements and shortens lead times, especially for low-volume, complex, or discontinued parts (Caldas *et al.*, 2019; Velázquez *et al.*, 2020). It also improves responsiveness to dynamic customer specifications while offering cost advantages in specific use cases (W. Li *et al.*, 2024). However, implementing mass customization strategies must still meet sector-specific regulatory requirements, particularly in safety-critical industries, where consistency and traceability are essential. As customer preferences increasingly shape product requirements, the need for scalable and flexible AM systems continues to grow (Rindfleisch & Im, 2019).

Hence, customization in AM is governed by three interrelated enablers: alignment with industry-specific design demands, seamless integration with digital systems, and the ability to adapt supply chains for greater responsiveness and efficiency. However, the impact of these enablers varies across operational contexts. For example, while digital integration enhances design flexibility and

precision, its effectiveness depends on data quality, system interoperability, and organizational capabilities. Similarly, supply chain flexibility can improve responsiveness, but may introduce challenges related to quality consistency and regulatory compliance in safety-critical industries. The effectiveness of customization therefore depends on balancing design flexibility with operational integration and regulatory consistency across the DSP ecosystem. High demand for complex, customized, or low-volume components acts as a market pull factor that encourages the adoption of on-demand manufacturing capabilities, thereby enhancing DSP ecosystem readiness.

Hypothesis 9 (H9): Customization Needs have a positive impact on shaping a successful DSP ecosystem.

2.10 Sustainability and Circular Economy Principles

AM offers strong potential to align spare parts management with circular economy goals through three key enablers: material efficiency, lifecycle extension, and localized production. AM can reduce waste by 35–80% via topology optimization and advanced design strategies (Prathyusha & Babu, 2022). Though energy-intensive processes, especially in metal AM can offset these gains (Liao & Cooper, 2021). Technologies like Wire Arc Additive Manufacturing (WAAM) and process parameter optimization enhance energy efficiency (Balidas *et al.*, 2024), while further research is needed to standardize energy metrics and improve multi-material circularity (Monteiro *et al.*, 2022).

AM also extends product lifespans by enabling high-precision remanufacturing, especially in aerospace and other high-value sectors (Top *et al.*, 2023). Integration with Industry 4.0 and AI enhances repair strategies and enables intelligent decision-making across the lifecycle (Fofou *et al.*, 2021). Additionally, recycled and bio-based materials such as PLA, ABS, PET, and wood composites are showing comparable performance to virgin materials, offering new avenues for sustainable production (Pinho *et al.*, 2020). However, variability in recycled material quality remains a concern (Djonyabe Habiba *et al.*, 2024).

Localized AM production shortens supply chains, cuts transportation emissions by up to 85.59% (Top *et al.*, 2023), and reduces warehousing and inventory costs (Cui *et al.*, 2021). AM integrated with digital inventory systems supports lean practices and just-in-time manufacturing (Lakshmanan *et al.*, 2023). In contrast, AM is generally more sustainable for low-volume, complex parts (Jung *et al.*, 2023). Its lifecycle impacts are highly context-dependent and sensitive to process choices (Liao *et al.*, 2023).

Despite these benefits, the sustainability impact of AM remains highly context-dependent. For instance, while material efficiency and waste reduction offer clear environmental advantages, energy-intensive processes, particularly in metal AM, may offset these gains depending on process selection and scale. Similarly, localized production reduces transportation emissions, yet its overall sustainability performance varies based on energy sources, material choices, and production volumes. These variations indicate that sustainability outcomes are not inherent to AM itself, but depend on the interaction between design strategies, process parameters, and supply chain configurations. The sustainability impact of AM is therefore

highly dependent on production context, process selection, and supply chain configuration rather than on the technology alone. Minimizing material waste and shortening transportation distances inherently reduce environmental footprints, offering a strong ecological incentive for supply network transformation.

Hypothesis 10 (H10): Sustainability and Circular Economy Principles have a positive impact on shaping a successful DSP ecosystem.

2.11 Risk Management

AM offers both prospects and obstacles in risk management. Key risks include cybersecurity concerns, quality control challenges, and supply chain vulnerabilities (Gupta *et al.*, 2020; Leso *et al.*, 2021). Researchers suggest multiple strategies to mitigate these risks, including the application of the NIST Risk Management Framework (Gibbons *et al.*, 2024), the utilization of fuzzy logic-based models for risk evaluation (Moreno-Cabezali & Fernandez-Crehuet, 2020), and the implementation of layered security protocols for data asset management (Milaat & Lubell, 2024). These structured frameworks provide a critical foundation for identifying, assessing, and mitigating risks across the AM lifecycle.

Cybersecurity in digital manufacturing environments has become increasingly important, especially as AM relies on digital design files and cloud-based platforms. Effective protection of intellectual property and system integrity requires not only encryption and access control, but also proactive detection of threats and anomalies (S. S. Babu *et al.*, 2022; Milaat & Lubell, 2024). This reinforces the need for comprehensive cybersecurity protocols to safeguard both digital files and manufacturing systems.

In addition, the flexibility of AM technologies has demonstrated value in mitigating supply chain risks, particularly during disruptions such as the COVID-19 pandemic by enabling localized production and reducing dependence on global logistics (Meyer *et al.*, 2022). These capabilities underscore the importance of developing operational strategies that anticipate and mitigate disruptions to critical infrastructure and spare parts delivery.

Occupational health concerns, such as emissions from AM processes, further emphasize the importance of a comprehensive risk strategy that includes both technological safeguards and human-centered protections (Leso *et al.*, 2021). Ultimately, effective risk management in AM requires a holistic approach, combining digital security, real-time quality assurance, and resilience planning to ensure safe and reliable spare parts production.

Taken together, these studies emphasize the need for integrated risk management approaches that combine cybersecurity, operational resilience, and supply chain contingency planning. However, the effectiveness of these approaches varies depending on the level of system integration and organizational readiness. For example, strong cybersecurity measures may protect digital assets, but without corresponding quality assurance and operational controls, risks related to production variability and reliability may persist. Similarly, supply chain resilience strategies can reduce disruption risks, yet their success depends on coordination with digital infrastructure and data integrity mechanisms. Effective AM risk mitigation therefore requires coordinated governance across cybersecurity, operational

reliability, and supply chain resilience mechanisms. Formalized cybersecurity protocols and risk management frameworks help preserve operational continuity, reduce implementation uncertainty, and support network stability during technology adoption.

Hypothesis 11 (H11): Risk Management has a positive impact on shaping a successful DSP ecosystem.

2.12 Vendor Support

Vendor support is a fundamental element in the execution and expansion of DSP systems utilizing AM. As AM technologies grow more complex and integrated into deep industrial systems, organizations are increasingly dependent on vendors not only for equipment and materials but also for continuous technical expertise, software updates, and operational support (Naghshineh & Carvalho, 2022), (Pakkala *et al.*, 2024). This reliance highlights the significance of strategic vendor partnerships that beyond the moment of acquisition.

Reliable vendor engagement enhances system stability and responsiveness by ensuring access to maintenance services, upgrades, and process optimization tools throughout the lifecycle of DSP solutions. Research has shown that inadequate vendor support can lead to delays, operational inefficiencies, and insufficient responses to emerging challenges, especially in sectors with strict maintenance regulations including aerospace, healthcare, and energy (Chekurov *et al.*, 2021; Pakkala *et al.*, 2024).

A significant issue in the adoption of AM is vendor lock-in, when proprietary software, materials, or machine settings limit the user's capacity to transition to alternative vendors (Jimo *et al.*, 2022). This lock-in can result in increased long-term operational expenses, diminished innovative adaptability, and risk of supply chain disruptions. To mitigate these risks, frameworks such as the CVL (Cloud Vendor Lock-in) model have been established to evaluate and reduce the strategic risks associated with vendor dependency (Alhosban *et al.*, 2024).

Additionally, AM disrupts traditional buyer-supplier relationships and sourcing techniques, frequently necessitating the development of new procurement models customized for the digital supply chain (Meyer *et al.*, 2020). The new models necessitate ongoing vendor collaborations that exceed transactional relationships, focusing instead on co-development, shared expertise, and lifetime support.

As AM-enabled digital ecosystems advance, particularly those incorporating Industry 4.0 technologies, suppliers are anticipated to enhance the cybersecurity and data integrity of digital production environments (Gupta *et al.*, 2020). The transition to cyber-physical integration necessitates that vendors contribute to maintaining secure system interoperability and safeguarding sensitive digital assets, including design files and production data.

Collectively, the literature indicates that vendor support extends beyond equipment provision to include long-term technical assistance, software integration, and strategic partnerships. However, the impact of vendor support varies depending on the level of dependency and system integration. For instance, strong vendor relationships can enhance system performance and reliability, yet excessive reliance may lead to vendor lock-in, limiting flexibility and increasing long-term operational risks. Similarly, while advanced vendor-driven solutions improve technological

capabilities, their effectiveness depends on interoperability with existing systems and organizational readiness. Vendor support therefore functions simultaneously as a source of operational enablement and a potential source of strategic dependency within DSP ecosystems. Continuous technical assistance and dependable after-sales maintenance from software and hardware vendors reduce investment risk and accelerate the deployment of DSP technologies.

Hypothesis 12 (H12): Vendor Support has a positive impact on shaping a successful DSP ecosystem.

2.13 Collaboration & Partnerships

Collaboration and partnerships are essential for the effective acceptance and expansion of DSP ecosystems. Digital ecosystems are gradually changing conventional supply chains into integrated, collaborative networks that generate new value propositions and business models (Bharadwaj & Yeo, 2020; Stonig *et al.*, 2022). This transformation requires a transition from conventional hierarchical models to dynamic collaborations and open innovation strategies (Rocha *et al.*, 2021). Research indicates that successful digital service delivery relies on stakeholder collaboration, data sharing, and the co-development of standardized practices (Tribello *et al.*, 2024). These elements reflect the need for structured stakeholder engagement during the development and deployment of DSP systems.

Manufacturing companies are implementing digital platforms, intelligent contracting systems, and Industry 4.0 technologies to create demand-responsive collaborative frameworks that promote innovation and expansion (Kazantsev *et al.*, 2023). The development of these frameworks often includes the implementation of data-sharing mechanisms and standardization initiatives, demonstrating the importance of collaborative governance structures and shared digital infrastructure.

While the transition to these ecosystems presents challenges in stakeholder alignment, governance, and integration of diverse knowledge bases (Tribello *et al.*, 2024), when executed effectively, collaborative ecosystems can unlock competitive advantages, elevate customer experiences, and drive DSP innovation (Metsä-Kortelainen *et al.*, 2020; Rocha *et al.*, 2021). Further evidence demonstrates that collaboration across disciplines and sectors promotes shared learning and decreases redundancy. Multidisciplinary collaboration in product development promotes innovation and cross-functional integration (Mulder-Nijkamp & de Koeijer, 2022), whereas ecosystem standardization enhances technical and organizational compatibility (Costabile *et al.*, 2022). Overall, prior studies emphasize the importance of collaborative networks, data-sharing platforms, and ecosystem governance structures. However, their effectiveness varies depending on the level of coordination among stakeholders and the maturity of the supporting digital infrastructure. For example, while collaboration can enhance innovation and knowledge sharing, misalignment in governance structures and data standards may limit its effectiveness. Similarly, cross-sector partnerships can drive ecosystem development, yet their success depends on the integration of technological, operational, and strategic objectives. The success of collaborative DSP ecosystems therefore depends on the degree of coordination between governance structures, digital infrastructure, and stakeholder objectives. Inter-

organizational information networks and shared data repositories help standardize operational practices across firms, significantly accelerating collective ecosystem growth.

Hypothesis 13 (H13): Collaboration & Partnerships have a positive impact on shaping a successful DSP ecosystem.

The thirteen ecosystem factors identified in this study represent interconnected technological, operational, strategic, and institutional dimensions of DSP adoption rather than independent drivers. Prior research suggests that improvements in one area, such as technological capability, infrastructure readiness, or regulatory compliance, often influence the development of other ecosystem capabilities. As a result, these factors are expected to interact and reinforce one another within a broader ecosystem context. To capture these interdependencies and evaluate the extent to which the proposed factors are related, this study examines the correlations among the independent constructs.

Hypothesis 14 (H14): There are significant correlations among the independent factors influencing the successful readiness of a DSP ecosystem in the UAE.

Despite the extensive body of research reviewed across the thirteen ecosystem dimensions, a comprehensive synthesis of the additive manufacturing and digital spare parts literature reveals three important gaps that continue to limit theoretical and practical advancement:

- (1) **Fragmentation of Ecosystem Enablers:** Existing studies predominantly focus on technological, material, operational, or logistical factors in isolation rather than examining DSP adoption as an integrated ecosystem. While prior research provides valuable insights into individual enablers such as material performance, infrastructure readiness, quality assurance, and regulatory compliance, limited attention has been given to understanding how these factors collectively influence DSP ecosystem readiness.
- (2) **Context-Dependent and Inconsistent Findings:** The literature reports mixed and often context-dependent findings regarding the influence of several ecosystem factors. For example, material availability, scalability, and quality assurance are frequently associated with improved adoption potential; however, their effects vary according to certification requirements, regulatory maturity, operational conditions, and industry context. These inconsistencies indicate that the influence of individual factors cannot be fully understood without considering the broader ecosystem environment in which they operate.
- (3) **Limited Empirical Validation of Ecosystem Relationships:** Although numerous conceptual frameworks, maturity models, and case studies have been proposed, relatively few studies have employed quantitative structural modeling approaches to simultaneously evaluate the relationships among multiple DSP ecosystem factors and their influence on adoption readiness. Consequently, limited empirical evidence exists regarding the relative importance of these factors and the extent to which they reinforce or constrain one another within a DSP ecosystem.

To address the identified gaps, this study develops and empirically evaluates a DSP ecosystem readiness framework. First, it synthesizes the fragmented literature into thirteen ecosystem factors operationalized through 39

measurable indicators, providing an integrated representation of each dimension of DSP adoption as summarized in Appendix A (Table A1). Second, using Structural Equation Modeling (SEM) and empirical data collected from 162 industry professionals, the study examines both the direct influence of these factors on DSP ecosystem readiness and the interrelationships among them. By doing so, the study addresses the limited empirical evidence regarding ecosystem-level interactions and provides a structured framework for understanding the drivers of DSP ecosystem readiness and their interrelationships.

3. METHODOLOGY

This study employed a structured, multi-phase methodology to develop and validate a framework for DSP ecosystem readiness in the UAE. Following an extensive literature review, 13 critical ecosystem factors were identified and operationalized into 39 measurable indicators.

- (1) **Step 1: Data Collection.** A structured questionnaire was developed and distributed across key UAE industries. The collected data were analyzed using SEM to examine how these factors interact and influence ecosystem readiness. This step is essential for building an empirically supported framework that reflects the dynamic structure of the DSP ecosystem and helps interpret ecosystem dynamics and inform future research and industry practice. Several procedural steps were implemented during the survey design to reduce potential common method bias. These include ensuring respondent anonymity, structuring the questionnaire clearly, and separating the measurement of different constructs within the survey instrument. These measures reduce the likelihood of response bias and improve the reliability of the collected data.
- (2) **Step 2: Data Validation and Reliability.** The collected data underwent rigorous validation procedures to ensure the reliability and validity of the survey instrument. The Kaiser–Meyer–Olkin (KMO) test was used to measure the sampling adequacy of each variable in the model. Cronbach’s alpha (α) was employed to assess internal consistency, selected for its simplicity, interpretability, and proven suitability for Likert-scale questionnaires. Additionally, convergent validity was established through Composite Reliability (CR) and Average Variance Extracted (AVE) analyses, both widely used in SEM. CR assessed the internal consistency of items measuring the same construct, while AVE determined the amount of variance in the construct explained by the items compared to measurement error. Discriminant validity was further evaluated using the Heterotrait–Monotrait (HTMT) ratio of correlations to ensure that the constructs are empirically distinct despite their conceptual relatedness. Furthermore, to address potential common method bias, Harman’s single-factor test was conducted as a statistical assessment.
- (3) **Step 3: Measurement Model Assessment.** After data validation, Confirmatory Factor Analysis (CFA) was employed to confirm the latent constructs underlying the DSP ecosystem, simultaneously testing the validity

of the proposed measurement model. CFA was chosen for its strength in model fit assessment and theory testing, offering a more robust alternative to exploratory factor analysis for this study. This was followed by an assessment of content validity through the examination of standardized factor loadings to ensure the chosen indicators accurately represented their corresponding constructs.

- (4) **Step 4: Structural Model Testing.** Subsequently, Structural Equation Modeling (SEM), by integrating factor analysis and path analysis, provided a comprehensive analysis for evaluating both the measurement model and the hypothesized structural relationships. SEM was utilized to examine the causal relationships among the 13 ecosystem factors (e.g., technological compatibility, infrastructure readiness, vendor support, cost, risk management, scalability), identifying the strength and significance of their interactions and their influence on overall DSP ecosystem readiness in the UAE. This was followed by goodness-of-fit testing to validate the structural model. In addition, univariate statistical analysis was conducted to explore whether perceptions of key factors varied by organizational characteristics such as industry sector or company size.

This methodological design ensures statistical rigor while maintaining contextual relevance, enabling the analysis of systemic interdependencies and generating insights to guide managerial decision-making and policy formulation. The next section presents the empirical results of this analysis.

4. RESULTS

This section summarizes the findings from the SEM analysis, highlighting how the 13 ecosystem factors interact to influence DSP readiness in the UAE. It identifies key relationships, validates the measurement model, and reveals which factors most strongly impact ecosystem readiness.

4.1 Step 1: Data Collection

According to the literature review presented in the previous section, each of the 13 factors influencing the readiness of DSP was identified and supported through a comprehensive review of relevant academic and industry studies. As outlined in Appendix A (Table A1), each factor was operationalized through three indicators, derived either directly from the literature or introduced by domain experts and subsequently reinforced by supporting research. These indicators were formulated as individual items in the questionnaire using a five-point Likert scale, designed to assess the degree to which each factor is perceived to influence the readiness and implementation of DSP technologies.

To ensure comprehensive data collection across relevant sectors, the study employed a purposive snowball sampling strategy, enabling the targeted distribution of the questionnaire to professionals with relevant experience in manufacturing, energy, aerospace, healthcare, and automotive industries. The questionnaire was disseminated via Google Forms and distributed to stakeholders with varying roles, organizational levels, and technical expertise. In total, 162 valid responses were collected and analyzed for the SEM phase.

4.1.1 Respondent's Demographic Information

A total of 162 participants completed the survey, representing a broad range of industries relevant to DSP and additive manufacturing. Male respondents comprised 77.78% of the total sample, while female respondents accounted for 22.22%.

These included key sectors such as energy, healthcare, aerospace, automotive, and manufacturing, with the following distribution: 35.19% from energy, 41.98% from healthcare, 4.32% from aerospace, 11.73% from automotive, and 6.79% from manufacturing.

Most participants (67.28%) were between the ages of 35 and 44, indicating that the majority of respondents are mid-career professionals actively contributing to industrial digitalization efforts in the UAE. Regarding educational qualifications, 64.81% of respondents held undergraduate degrees, while 35.19% held postgraduate degrees, reflecting a technically proficient and academically mature participant pool.

In terms of professional experience, the respondents were distributed as follows: 7.41% had 1–7 years of experience, 53.09% had 8–15 years, 34.57% had 16–23 years, and 1.85% had 24 years or more. This spread illustrates balanced representation across experience levels, providing diverse insights into the readiness challenges and opportunities within DSP ecosystems.

Additionally, participants represented organizations of varying sizes, categorized as follows: 4.32% from organizations with 1–50 employees, 19.14% from 51–500 employees, 43.21% from 500–1000 employees, 30.25% from 1000–5000 employees, and 3.09% from organizations with more than 5000 employees. This distribution supports a comprehensive understanding of digital readiness dynamics across both small and large enterprises.

4.2 Step 2: Data Validation and Reliability

This step represents a critical preliminary phase prior to conducting CFA and SEM, as it ensures the validity and reliability of the collected data. Appendix A (Table A2) presents the results of the validity and reliability assessments, which include the standardized factor loadings of each indicator within its respective construct, the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, Cronbach's alpha (α), Composite Reliability (CR), and Average Variance Extracted (AVE).

- The KMO test was used to determine whether the sample size was adequate for SEM analysis. A KMO value between 0.7 and 1.0 is generally considered sufficient. In this study, the KMO value was 0.82964780, confirming the adequacy of the sample for factor analysis.
- Cronbach's alpha was calculated to assess the internal consistency of each factor, indicating how well the items grouped under the same construct are correlated. Values above 0.7 are considered acceptable. As shown in Appendix A (Table A2), Cronbach's alpha values ranged between 0.95939 and 0.978791, confirming good internal consistency.
- In addition, Composite Reliability (CR) was calculated to assess the reliability of the indicators in representing each construct. CR is considered more robust than Cronbach's alpha, and values above 0.7 indicate adequate reliability. The CR values for this study ranged from 0.81979 to 0.94595.

- The Average Variance Extracted (AVE) was computed to evaluate convergent validity by measuring the proportion of variance explained by the latent constructs relative to measurement error. An AVE value of 0.5 or higher is deemed acceptable. In this study, the AVE values ranged from 0.6029 to 0.85367.
- In addition, the adequacy of the sample size for CB-SEM was assessed based on established methodological guidance and prior empirical evidence. Hair et al. (2019) and Kline (2023) emphasize that sample size requirements in SEM are not determined by a single rule but rather depend on model characteristics such as factor loading magnitude, communality levels, and overall model fit. In particular, higher standardized loadings and strong measurement quality reduce the minimum sample size required for stable parameter estimation.

Furthermore, Monte Carlo simulation results reported by Wolf et al. (2013) demonstrate that acceptable sample sizes for SEM models can vary substantially depending on model conditions, with models exhibiting high factor loadings and strong reliability achieving adequate statistical power and estimation stability with relatively moderate sample sizes.

In the present study, the sample consists of 162 valid responses for a model including 39 observed indicators and multiple latent constructs. All standardized factor loadings exceed 0.92, indicating strong indicator reliability and high communalities. In addition, the model demonstrates satisfactory reliability (Cronbach's α , CR), convergent validity (AVE), and excellent fit indices. Based on the criteria outlined in prior SEM literature, these conditions support the adequacy of the sample size and indicate that the estimated parameters are stable and reliable despite the structural complexity of the model.

Discriminant validity was further assessed using the Heterotrait–Monotrait (HTMT) ratio of correlations, which is considered a more robust and widely accepted criterion for evaluating construct distinctiveness in SEM. As presented in Table 1, all HTMT values were below the conservative threshold of 0.85, with the highest observed value remaining well within acceptable limits, indicating that the constructs are empirically distinct despite their conceptual relatedness. This confirms that each factor captures a unique dimension of the DSP ecosystem, supporting the structural integrity of the proposed model and the results provide strong evidence of discriminant validity and confirm that the constructs are not empirically overlapping.

To further address potential common method bias, Harman's single-factor test was conducted. The results indicate that the first factor accounts for 18.70% of the total variance, which is well below the threshold of 50%. This suggests that common method bias is unlikely to significantly influence the results of the study.

In addition, to further assess potential multicollinearity among the predictors in the structural model, variance inflation factors (VIF) and tolerance statistics were calculated using construct composite scores, as shown in Table 2. The results indicate that VIF values range between 1.42 and 2.42, which are well below the commonly accepted threshold of 5 and even below the more conservative threshold of 3. In addition, all tolerance values exceed 0.2,

Table 1 HTMT Matrix for Discriminant Validity

Constructs	TC	MP	IR	C	S	Q	RC	IN	CN	SCE	RM	VS	CP
TC	—	0.49495	0.10856	0.03386	0.03175	0.03960	0.05692	0.05742	0.02762	0.05541	0.02711	0.03921	0.18852
MP	0.49495	—	0.60225	0.28603	0.23228	0.03510	0.05655	0.02990	0.01550	0.09421	0.05255	0.08684	0.18613
IR	0.10856	0.60225	—	0.62531	0.28628	0.03826	0.02856	0.04970	0.01811	0.05588	0.06119	0.08146	0.02864
C	0.03386	0.28603	0.62531	—	0.53035	0.08965	0.01918	0.07325	0.04216	0.03091	0.03146	0.05861	0.02137
S	0.03175	0.23228	0.28628	0.53035	—	0.44986	0.10563	0.18446	0.18354	0.15976	0.10414	0.17379	0.03697
Q	0.03960	0.03510	0.03826	0.08965	0.44986	—	0.50352	0.22097	0.15385	0.06274	0.15962	0.14577	0.06788
RC	0.05692	0.05655	0.02856	0.01918	0.10563	0.50352	—	0.58516	0.19372	0.14357	0.06415	0.05047	0.05658
IN	0.05742	0.02990	0.04970	0.07325	0.18446	0.22097	0.58516	—	0.49474	0.09509	0.10360	0.12015	0.04482
CN	0.02762	0.01550	0.01811	0.04216	0.18354	0.15385	0.19372	0.49474	—	0.49151	0.07394	0.02221	0.02503
SCE	0.05541	0.09421	0.05588	0.03091	0.15976	0.06274	0.14357	0.09509	0.49151	—	0.46928	0.14623	0.10508
RM	0.02711	0.05255	0.06119	0.03146	0.10414	0.15962	0.06415	0.10360	0.07394	0.46928	—	0.53151	0.03187
VS	0.03921	0.08684	0.08146	0.05861	0.17379	0.14577	0.05047	0.12015	0.02221	0.14623	0.53151	—	0.40560
CP	0.18852	0.18613	0.02864	0.02137	0.03697	0.06788	0.05658	0.04482	0.02503	0.10508	0.03187	0.40560	—

Table 2 Multicollinearity Diagnostics (VIF and Tolerance Values)

Variable	Tolerance	VIF
TC	0.70410	1.42024
MP	0.42700	2.34193
IR	0.41332	2.41942
CST	0.46904	2.13200
SCL	0.50154	1.99387
QAL	0.54533	1.83375
RC	0.46423	2.15412
IND	0.44076	2.26882
CN	0.49531	2.01892
SCE	0.46780	2.13768
RM	0.49108	2.03633
VS	0.52307	1.91179
CP	0.69465	1.439

Table 3 CFA Goodness of Fit Criteria

Criteria	Value
Standardized RMR (SRMR)	0.0255
RMSE Estimate	0.0277
Bentler Comparative Fit Index (CFI)	0.9909

confirming the absence of multicollinearity concerns. These findings indicate that the structural relationships in the model are stable and not affected by multicollinearity, and that the observed negative coefficients reflect genuine structural effects rather than statistical artifacts arising from predictor intercorrelations.

Together, these results confirm the robustness of both the measurement and structural models, supporting their suitability for subsequent CFA and SEM analysis.

4.3 Step 3: Measurement Model Assessment

This subsection presents the results of the CFA as outlined in Table 3. The objective is to assess the content validity of the indicators and evaluate the overall goodness-of-fit of the CFA model. Content validity is determined through the CFA's standardized parameter estimates (factor loadings). A threshold of 0.70 or higher is typically considered acceptable. As shown in Appendix A (Table A2), all indicator loadings fall within the range of 0.92917 to 0.97564, confirming that each indicator adequately reflects its corresponding latent construct within the DSP ecosystem. Additionally, the p-values for all indicators are below 0.05, indicating their statistical significance. To validate the

overall model, several fit indices were evaluated as shown in Table 3:

- Standardized Root Mean Square Residual (SRMR), where values ≤ 0.05 suggest good fit (SRMR = 0.0255).
- Root Mean Square residual (RMSE) Estimate, where the value of 0.05 or less is preferred.
- Comparative Fit Index (CFI), which should also be ≥ 0.90 (CFI = 0.9909).

These goodness-of-fit values demonstrate that the CFA model meets the acceptable thresholds for model adequacy. The findings confirm both the validity of the indicators and the overall structural coherence of the model, providing a strong foundation for further analysis using SEM.

4.4 Step 4: Structural Model Testing

In this subsection, and based on the literature review and expert input, it was hypothesized that various technological, operational, and strategic factors significantly influence the development and readiness of a successful DSP ecosystem in the UAE. The SEM model in Figure 1 was constructed to evaluate both the direct effects of the thirteen ecosystem factors on DSP ecosystem readiness (H1–H13) and the interrelationships among these factors (H14).

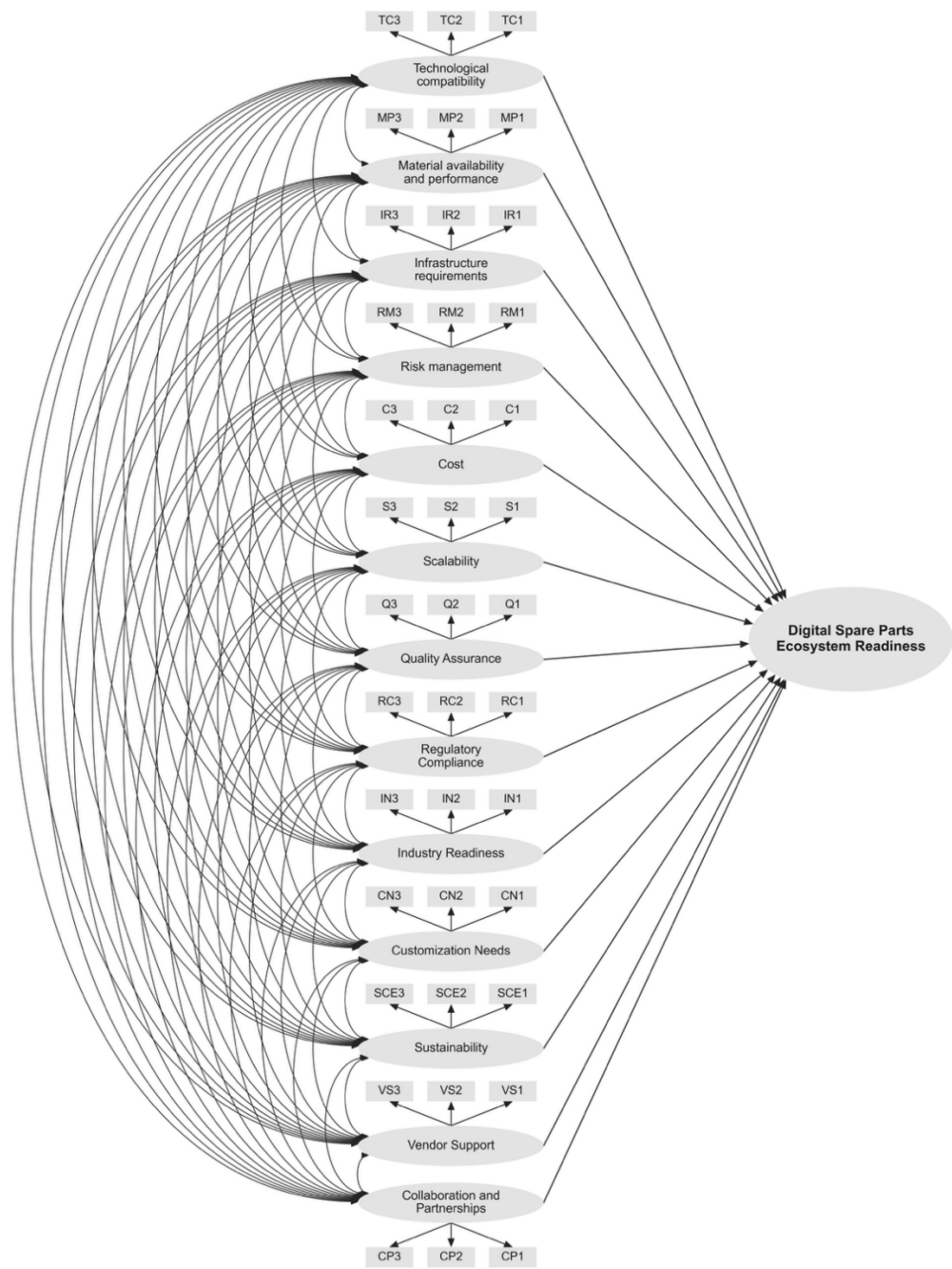


Figure 1 SEM Model for DSP Readiness

The model was applied to data collected from 162 participants across key industrial sectors, including energy, aerospace, automotive, manufacturing, and healthcare. The primary objective was to examine how the proposed ecosystem factors and their associated indicators contribute to shaping an integrated and scalable DSP ecosystem, assess their relative importance in influencing DSP ecosystem readiness, and evaluate the relationships among the independent constructs. The results of the hypothesis testing are presented in the following sections.

The SEM model was fitted to the data using PROC CALIS in SAS software. The model evaluates the influence of 13 independent factors on the successful shaping and enablement of a DSP Ecosystem in the UAE. The standardized path coefficients and their statistical

Table 4 SEM Goodness of Fit Criteria	
Criteria	Value
Standardized RMR (SRMR)	0.0252
RMSEA Estimate	0.0272
Bentler Comparative Fit Index (CFI)	0.9911

significance are summarized in Appendix A (Table A3). All indicators demonstrated statistically significant factor loadings ($p\text{-value} < 0.05$), confirming their validity in measuring the constructs and supporting the hypothesized model structure. Moreover, the model's goodness-of-fit indices are shown in Table 4 indicating $SRMR = 0.0252$, $RMSEA = 0.0272$, and $CFI = 0.9911$. These values are within acceptable thresholds, demonstrating an overall good model fit.

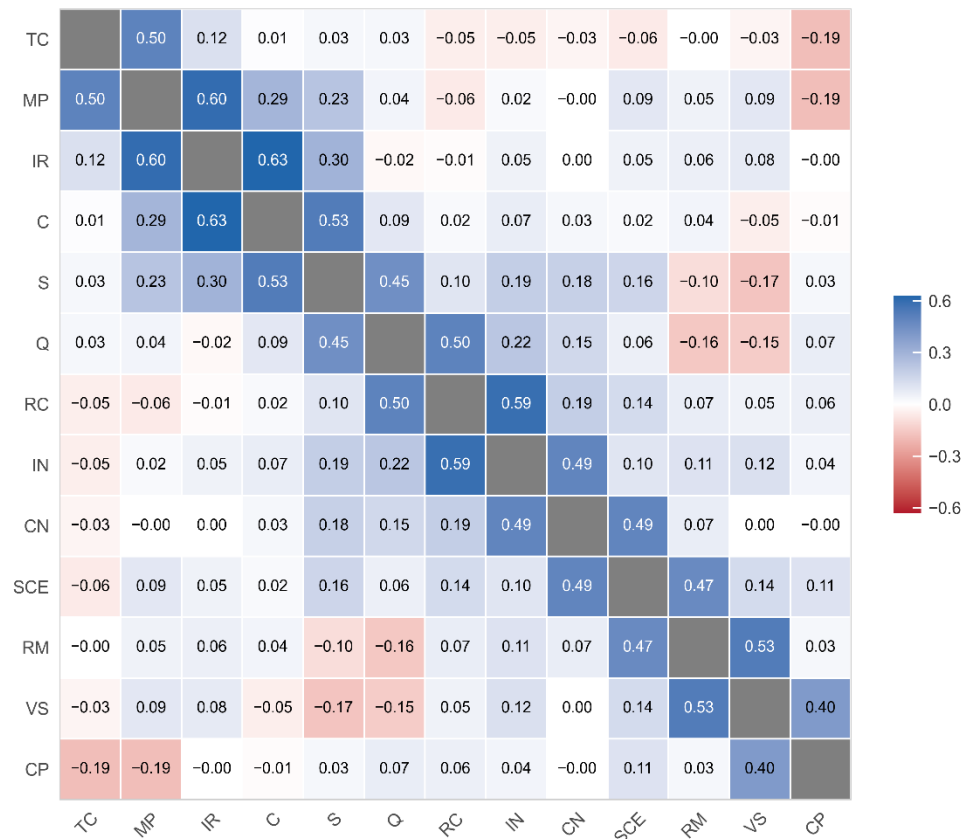


Figure 2 Correlation Heatmap of DSP Factors

To test Hypotheses H1 through H13, which posit that each independent factor exerts a positive influence on the successful readiness of a DSP ecosystem in the UAE, the standardized path coefficients from each factor to the “Readiness” construct were examined for both magnitude and statistical significance.

The SEM results provide strong support for the majority of the hypothesized positive relationships. Specifically, Technological Compatibility (H1), Infrastructure Requirements (H3), Cost (H4), Quality Assurance (H6), Regulatory Compliance (H7), Customization Needs (H9), Vendor Support (H12), and Collaboration & Partnerships (H13) all exhibit significant and positive standardized path coefficients to Readiness ($p < 0.05$). This indicates that improvements in these factors are associated with increased readiness for DSP ecosystem adoption.

However, several hypotheses are not supported by the data. Material Availability & Performance (H2), Scalability (H5), and Industry Readiness (H8) show significant but negative path coefficients, suggesting that higher levels of these factors are unexpectedly associated with lower readiness. This counterintuitive finding may reflect complex dynamics, such as potential resource misalignments or the premature development of certain capabilities relative to the broader ecosystem. In the UAE context, this can be interpreted in light of the evolving nature of additive manufacturing capabilities, the presence of multiple regulatory and operational environments, and the reliance on external technical expertise in certain industrial settings. These conditions may create situations where advancements

in specific areas do not immediately translate into overall ecosystem readiness. At the same time, the positive effects observed for regulatory compliance and vendor support can be interpreted in light of national initiatives such as Operation 300bn and the Dubai 3D Printing Strategy, which emphasize regulatory development, industrial standardization, and ecosystem partnerships. These findings suggest that such policy directions may be supporting governance structures and enabling mechanisms that facilitate DSP ecosystem adoption in the UAE. Further qualitative research may be needed to explore these relationships in greater depth.

Additionally, Sustainability and Circular Economy Principles (H10) and Risk Management (H11) do not have statistically significant effects on Readiness, as indicated by their high p -values. This suggests that, within the current model and context, these factors may not be primary drivers of DSP ecosystem readiness, or their effects may be indirect or mediated by other variables not captured in this analysis.

Moreover, to examine the interrelationships among the independent variables and to test Hypothesis H14, a comprehensive pairwise correlation analysis was conducted. This analysis assessed the standardized correlations between all unique pairs of the 13 independent factors included in the SEM. In total, 78 unique pairwise relationships were evaluated for both the strength and statistical significance of their associations.

The results are presented visually in Figure 2, which displays the correlation heatmap showing the strength and direction of relationships between the factors, and Figure 3, which presents the corresponding significance (p -value)

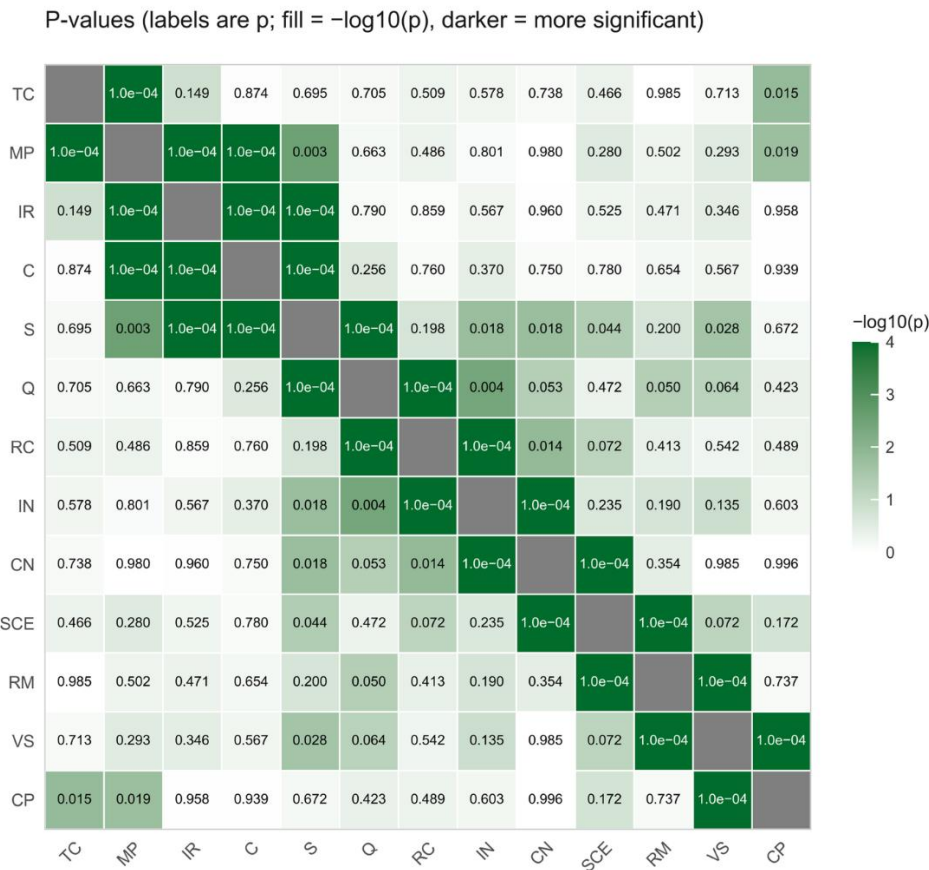


Figure 3 Significance Heatmap (p-Values) of DSP Factors

heatmap. Together, these visualizations provide a more intuitive understanding of both the magnitude and the reliability of the observed associations across the factors.

The results of the correlation analysis revealed a mixed pattern of interdependencies among the independent factors. Of the 78 pairwise relationships examined, 22 demonstrated statistically significant correlations at the $p < 0.05$ level, indicating that a subset of the independent factors exhibits significant interrelationships. These significant correlations suggest that certain factors may not operate in isolation but rather influence each other in the context of DSP Ecosystem adoption.

Specifically, several factor pairs exhibited strong and highly significant positive correlations. For example, the correlation between Technological Compatibility (TC) and Material Availability & Performance (MP) was $r = 0.498$ ($p < .0001$), suggesting that higher levels of technological competence are associated with greater Material Availability & Performance. Similarly, strong positive correlations were observed between Material Availability & Performance (MP) and Infrastructure Readiness (IR) ($r = 0.603$, $p < .0001$), Infrastructure Readiness (IR) and Cost (C) ($r = 0.628$, $p < .0001$), and Cost (C) and Scalability (S) ($r = 0.529$, $p < .0001$). These findings indicate that these factors may be mutually reinforcing in their influence on DSP Ecosystem adoption.

However, the majority of factor pairs (56 out of 78) did not exhibit statistically significant correlations at the $p < 0.05$ level. These non-significant relationships suggest that several independent factors may operate relatively

independently within the DSP ecosystem. For instance, the correlations between Technological Compatibility (TC) and Cost (C) ($r = 0.013$, $p = 0.876$), Technological Compatibility (TC) and Scalability (S) ($r = 0.032$, $p = 0.697$), and Infrastructure Readiness (IR) and Quality (Q) ($r = -0.022$, $p = 0.785$) were not statistically significant.

At the same time, some factor pairs exhibit moderate and statistically significant correlations, indicating the presence of interdependencies among certain ecosystem dimensions. This reflects the interconnected nature of DSP ecosystem factors rather than redundancy between constructs. To ensure that these relationships do not indicate a lack of construct distinctiveness, discriminant validity was formally assessed using the Heterotrait–Monotrait (HTMT) ratio of correlations. As presented in Table 3, all HTMT values are below the conservative threshold of 0.85, confirming that the constructs remain empirically distinct despite these observed associations. These findings suggest that DSP ecosystem readiness is shaped by a combination of interrelated and independent factors, highlighting the complexity of interactions across technological, operational, and strategic dimensions.

5. DISCUSSION

This study set out to identify, validate, and empirically test the key factors influencing DSP ecosystem readiness using data collected from industry professionals in the UAE. The research process began with a rigorous literature review and expert consultation, resulting in the identification and refinement of 13 core factors, each operationalized through

three carefully selected indicators. These indicators were designed to capture the multifaceted nature of DSP adoption, ensuring both academic rigor and practical relevance.

The measurement model was subjected to thorough validation using CFA. The results demonstrated excellent construct validity and reliability, as evidenced by high standardized factor loadings (all >0.92), strong Cronbach's alpha values (all >0.96), robust CR, and satisfactory AVE. The model's goodness-of-fit indices (SRMR = 0.0255, RMSEA = 0.0277, CFI = 0.9909) further confirmed the adequacy of the measurement structure, providing a solid foundation for subsequent structural analysis.

The SEM tested 13 hypotheses (H1–H13), each positing a positive impact of an independent factor on DSP ecosystem readiness. The results provide strong empirical support for the majority of these hypotheses. Specifically, Technological Compatibility, Infrastructure Requirements, Cost, Quality Assurance, Regulatory Compliance, Customization Needs, Vendor Support, and Collaboration & Partnerships all exhibited significant and positive effects on readiness. These findings align with the extant literature, underscoring the importance of technological integration, regulatory alignment, cost management, and collaborative networks in driving digital transformation within spare parts supply chains.

However, the analysis also revealed several unexpected outcomes. Material Availability & Performance, Scalability, and Industry Readiness demonstrated significant but negative path coefficients, suggesting that, within the current ecosystem conditions, higher levels of these factors may be associated with lower readiness for DSP adoption. One possible explanation relates to ecosystem maturity dynamics, where developments in certain capabilities may progress faster than the supporting institutional and operational environment required for effective implementation. For example, greater material availability does not necessarily translate into adoption readiness if supporting elements such as certification frameworks, testing infrastructure, and regulatory approval mechanisms remain underdeveloped. In such situations, the availability of materials without standardized validation pathways may increase uncertainty for organizations considering DSP implementation. Similarly, rapid scalability initiatives may introduce operational inconsistencies when implementation maturity varies across industrial environments and organizations.

In the UAE context, these dynamics may reflect the country's accelerated industrial transformation under initiatives such as Operation 300bn and the Dubai 3D Printing Strategy. The UAE manufacturing landscape includes more than 40 industrial and free zones operating across different emirates and regulatory settings, while individual emirates continue to implement tailored industrial initiatives aligned with local priorities. These conditions may create variations in operational readiness, certification practices, and technology deployment maturity across organizations. In addition, the rapid expansion of advanced manufacturing capabilities may progress faster than the supporting institutional infrastructure, workforce capabilities, and standardized validation systems required for large-scale DSP implementation (Ministry of Investment & Ministry of Industry and Advanced Technology, 2026). As a

result, improvements in material availability, scalability, or technical capability may not immediately translate into higher overall DSP ecosystem readiness.

In contrast, the positive effects observed for regulatory compliance and vendor support suggest that ongoing UAE investments in industrial governance, standardization, and technology enablement may already be contributing to stronger coordination between organizations, vendors, and regulatory bodies within the DSP ecosystem. This includes initiatives such as the Technology Transformation Program, certification bodies, testing facilities, and Industry 4.0 enablement centers, which aim to strengthen compliance readiness, technology integration, and ecosystem coordination across manufacturing sectors.

Similarly, investments in scalability may introduce operational complexity when the surrounding ecosystem such as quality assurance systems, supply chain integration, and digital infrastructure has not yet reached sufficient maturity. Attempts to scale production capacity before establishing stable process control, certification protocols, and workflow integration may therefore create inefficiencies rather than accelerate adoption. This dynamic may be particularly relevant in rapidly evolving industrial environments such as the UAE, where ecosystem development and operational capabilities may not always progress at the same pace.

The negative relationship observed for industry readiness may also reflect uneven technological preparedness across sectors. While organizations may demonstrate interest in additive manufacturing technologies, limitations in workforce expertise, operational integration, and institutional support may prevent this readiness from translating into effective ecosystem implementation. These findings suggest that DSP adoption depends not only on the presence of individual enablers but also on the balanced and coordinated development of the broader ecosystem. In the UAE context, this may reflect transitional dynamics where strategic initiatives and technological investments advance ahead of firm-level operational readiness. Additionally, Sustainability and Circular Economy Principles and Risk Management did not show significant direct effects on readiness, indicating that their influence may be more indirect or context-dependent.

The pairwise correlation analysis among the independent factors (H14) revealed a nuanced landscape of interrelationships. While 22 out of 78 unique pairs exhibited significant correlations, the majority did not, suggesting that many factors operate relatively independently. Notably, strong positive correlations were observed among certain technological and operational factors, indicating potential synergies that could be leveraged in ecosystem design. Conversely, the lack of significant correlations among other pairs highlights the need for targeted interventions that address specific barriers without assuming uniform interdependence across all factors.

These findings have several important implications. First, they highlight the multifactorial and context-sensitive nature of DSP ecosystem adoption, where not all theoretically important factors exert a positive or direct influence. Second, the results underscore the value of a robust measurement framework that integrates both literature-driven and expert-validated indicators, ensuring

that the model remains relevant to both academic inquiry and industry practice. Third, the observed negative and non-significant effects point to the need for further qualitative research to unpack the underlying mechanisms and contextual nuances that shape DSP ecosystem readiness across emerging digital manufacturing environments.

These findings can also be interpreted in light of national initiatives such as Operation 300bn and the Dubai 3D Printing Strategy, which emphasize regulatory development, industrial standardization, and ecosystem partnerships. The positive effects observed for regulatory compliance and vendor support suggest that these policy directions may be strengthening governance mechanisms and enabling greater coordination within the DSP ecosystem. Recent UAE investments in industrial governance and standardization initiatives including the Technology Transformation Program and the expansion of industrial support infrastructure such as certification bodies, testing facilities, and Industry 4.0 enablement centers further support this interpretation, as these initiatives are intended to improve coordination, compliance readiness, and technology integration across manufacturing sectors. At the same time, the mixed and counterintuitive findings associated with material availability, scalability, and industry readiness highlight the importance of aligning national strategic ambitions with firm-level operational and implementation capabilities to ensure effective DSP ecosystem adoption.

Despite the robustness of the statistical results, several limitations should be acknowledged. First, the study relies on cross-sectional survey data collected at a single point in time, which limits the ability to establish causal relationships among the constructs. Second, although the sample includes professionals from multiple industries, the findings are based on purposive sampling and may not fully capture the diversity of organizational contexts within the broader manufacturing ecosystem. Future research could extend this work using longitudinal data, larger cross-country samples, or mixed-method approaches to further validate and refine the proposed DSP ecosystem model.

In conclusion, this study advances the understanding of DSP ecosystem readiness by providing a validated, empirically tested model that captures the complexity of technological, operational, and strategic influences. The results provide analytical insights for researchers and industry practitioners seeking to better understand DSP ecosystem development and identify areas for future investigation and model refinement. While the model was validated using data collected from UAE-based industry professionals, the findings reflect broader ecosystem dynamics that may also apply to other emerging digital manufacturing environments. Future comparative studies across different national contexts would further clarify how institutional structures, industrial maturity, and policy environments influence DSP adoption readiness.

6. CONCLUSION AND RECOMMENDATIONS

This study advances the understanding of DSP adoption by developing and validating a structural model of ecosystem readiness in the UAE. The findings demonstrate that DSP readiness is shaped by a combination of technological, operational, and strategic enablers, with

technological compatibility, infrastructure readiness, cost, quality assurance, regulatory compliance, customization needs, vendor support, and collaboration emerging as the most influential drivers. At the same time, the study reveals that factors such as material availability and performance, scalability, and industry readiness may, under certain ecosystem conditions, constrain rather than accelerate adoption, highlighting the complexity and interdependence of readiness factors. These findings contribute to the literature by providing an integrated ecosystem perspective and empirically validating the relationships among thirteen ecosystem dimensions through SEM. From a practical perspective, the results suggest that organizations and policymakers should prioritize technological integration, infrastructure development, quality assurance, regulatory alignment, and collaborative partnerships while ensuring that investments in material capabilities, scalability initiatives, and industry readiness are supported by appropriate governance, validation mechanisms, and organizational capabilities. Although this study provides valuable insights, its cross-sectional design limits causal inference and its focus on the UAE may restrict generalizability to other contexts. Future research should employ longitudinal approaches and cross-country comparisons to further examine the evolution and transferability of DSP ecosystem readiness models.

CONFLICTS OF INTEREST

The authors declare that they have no known financial or non-financial conflicts of interest that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENTS

The data that support the findings of this study were collected through a structured survey of industry professionals in the United Arab Emirates. Due to confidentiality agreements and the inclusion of sensitive organizational information, the raw data are not publicly available. Aggregated and anonymized data may be made available from the corresponding author upon reasonable request and subject to institutional approval.

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Wadhah Alzahmi received her Ph.D. degree in Engineering Systems Management from the American University of Sharjah, United Arab Emirates. She holds a Master's degree in Innovation Management from the Mohammed bin Rashid School of Government and a bachelor's degree in applied science in Electronic Engineering Technology from the Higher Colleges of Technology. She is a Senior Specialist at the Dubai Electricity and Water Authority (DEWA), where she leads projects related to smart grids, electric vehicle infrastructure, and digital transformation initiatives. Her research interests include digital spare parts ecosystems, additive manufacturing, Industry 4.0 technologies, and innovation in energy systems.

Abdulrahim Shamayleh received the Ph.D. degree in industrial, systems and operations engineering from Arizona State University. He is a Certified Supply Chain Professional and an Instructor from the American Association for Operations Management. He is currently an Associate Professor of industrial engineering and engineering systems management at the American University of Sharjah. His research has appeared in *Computers and Industrial Engineering*, *Journal of Cleaner Production*, and *Sustainable Cities and Society*. His research interests include operation research in healthcare, scheduling, supply chain management, and facilities planning and design.

Appendix A. Supplementary Results

Table A1 DSP Ecosystem Factors with Indicators

Factor	Code	Selected Indicator	References
Technological Compatibility	TC1	Multi-Process Integration Capability	(Han & Lee, 2020), (Rabalo <i>et al.</i> , 2023)
	TC2	Automation and Smart Functionality	(Tamir <i>et al.</i> , 2023)
	TC3	Precision and Quality Control Mechanisms	(Snapp <i>et al.</i> , 2021), (Quigley <i>et al.</i> , 2023), (Trejo-Morales <i>et al.</i> , 2024)
Material Availability & Performance	MP1	Availability of materials	(Tetsuka & Shin, 2020), (Das <i>et al.</i> , 2016), (Olawumi <i>et al.</i> , 2023)
	MP2	Compatibility of materials with operational conditions	(Kantaros <i>et al.</i> , 2023), (Amini & Chang, 2018; V. V. P. Babu & Vinod Kumar, 2022), (Tuli <i>et al.</i> , 2024)
	MP3	Consistency in local access and certification of validated materials	(Kassab <i>et al.</i> , 2023), (Al Rashid & Koç, 2023), (Ferreira <i>et al.</i> , 2019; Meurer & Classen, 2021)
Infrastructure Requirements	IR1	Data Interoperability Readiness	(Bonnard <i>et al.</i> , 2018), (Perišić <i>et al.</i> , 2021; Perišić <i>et al.</i> , 2022)
	IR2	Software-Hardware Compatibility	(Kutin <i>et al.</i> , 2018), (Kim <i>et al.</i> , 2015), (Mhapsekar <i>et al.</i> , 2018; Prathyusha & Babu, 2022)
Cost	IR3	Workflow Integration Capability	(AbouelNour & Gupta, 2022)
	C1	Affordability of DSP technologies	(Moldovan <i>et al.</i> , 2018), (Bell, 2014), (Ajay <i>et al.</i> , 2016)
	C2	Cost optimization and lifecycle planning practices	(Fauth <i>et al.</i> , 2019), (Baumers <i>et al.</i> , 2017), (Kudelski <i>et al.</i> , 2017)
Scalability	C3	Alignment of cost models with sector needs	(Fauth <i>et al.</i> , 2019; Gkika <i>et al.</i> , 2022)
	S1	Flexibility of production systems for scale-up	(Tiwary <i>et al.</i> , 2021), (Klaeger & Telesh, 2020)
	S2	Integration of scalable processes into supply chains	(Cardeal <i>et al.</i> , 2022; Song & Zhang, 2020), (Chandima Ratnayake <i>et al.</i> , 2019; Deradjat & Minshall, 2015)
Quality Assurance	S3	Consistency in quality across scaled operations	(Goh <i>et al.</i> , 2024), (Kladovasilakis <i>et al.</i> , 2024)
	Q1	Consistency in material and part integrity	(Akande, 2015), (Patil <i>et al.</i> , 2015), (De Bruycker <i>et al.</i> , 2021; Gajewski <i>et al.</i> , 2023)
	Q2	Adoption of real-time monitoring and defect correction	(Gardner <i>et al.</i> , 2019; Ratnavel <i>et al.</i> , 2022), (Borish <i>et al.</i> , 2020), (AbouelNour & Gupta, 2022), (Jin <i>et al.</i> , 2020; Razaviarab <i>et al.</i> , 2019)
Regulatory Compliance	Q3	Compliance with industry-wide quality standards	(Mandache, 2019), (Galleguillos <i>et al.</i> , 2023), (Kawalkar <i>et al.</i> , 2022), (Schulenburg & Herold, 2020; Soete <i>et al.</i> , 2019)
	RC1	Compliance with Standards and Certification	(Gao <i>et al.</i> , 2015), (Frandsen <i>et al.</i> , 2020), (Ballardini <i>et al.</i> , 2018), (Nyika <i>et al.</i> , 2022)
	RC2	Regulatory Quality and Reliability Management	(Budzik <i>et al.</i> , 2021; Paxton, 2023), (Fang <i>et al.</i> , 2022; Tamir <i>et al.</i> , 2023), (Yang <i>et al.</i> , 2020), (Ballardini <i>et al.</i> , 2018; S. Li & Visscher, 2020)
Industry Readiness	RC3	Conformity to International Regulatory Frameworks	(Abeliansky <i>et al.</i> , 2020), (Ballardini <i>et al.</i> , 2018), (Mies <i>et al.</i> , 2016)
	IN1	Technological and Infrastructure Readiness	(Çınar <i>et al.</i> , 2021; De Carolis <i>et al.</i> , 2017), (Chekurov <i>et al.</i> , 2021), (Kretzschmar <i>et al.</i> , 2018)
	IN2	Workforce and Organizational Readiness	(Despeisse & Minshall, 2017; Mehta & Berdanier, 2019)
Customization Needs	IN3	Innovation Investment	(Kretzschmar <i>et al.</i> , 2018; Savastano <i>et al.</i> , 2016), (Flores Ituarte <i>et al.</i> , 2016)
	CN1	Industry-Specific Design Requirements	(Martinez <i>et al.</i> , 2022), (Mobarak <i>et al.</i> , 2023), (Coruzzolo <i>et al.</i> , 2022), (Beiderbeck <i>et al.</i> , 2018; Peron & Sgarbossa, 2021)
	CN2	Integration with Digital Technologies	(Kantaros & Ganetsos, 2024), (Montero <i>et al.</i> , 2020; Rešetar <i>et al.</i> , 2024), (de Brito <i>et al.</i> , 2020; Iraqi <i>et al.</i> , 2016)
Sustainability and Circular Economy Principles	CN3	Impact on Supply Chain Flexibility	(Caldas <i>et al.</i> , 2019; Velázquez <i>et al.</i> , 2020), (W. Li <i>et al.</i> , 2024), (Rindfleisch & Im, 2019)
	SCE1	Material Efficiency and Waste Reduction	(Jung <i>et al.</i> , 2023), (Prathyusha & Babu, 2022), (Liao & Cooper, 2021)
	SCE2	Lifecycle Extension through Repair/Remanufacturing	(Top <i>et al.</i> , 2023), (Fofou <i>et al.</i> , 2021), (Djonyabe Habiba <i>et al.</i> , 2024), (Pinho <i>et al.</i> , 2020)
	SCE3	Localized Production & Supply Chain Impact	(Top <i>et al.</i> , 2023), (Cui <i>et al.</i> , 2021), (Lakshmanan <i>et al.</i> , 2023), (Jung <i>et al.</i> , 2023), (Liao <i>et al.</i> , 2023)

Table A1 DSP Ecosystem Factors with Indicators (Cont'd)

Factor	Code	Selected Indicator	References
Risk Management	RM1	Adoption of structured risk management frameworks	(Gupta <i>et al.</i> , 2020; Leso <i>et al.</i> , 2021), (Gibbons <i>et al.</i> , 2024), (Milaat & Lubell, 2024)
	RM2	Implementation of cybersecurity protocols to protect digital spare part data	(S. S. Babu <i>et al.</i> , 2022; Milaat & Lubell, 2024)
	RM3	Operational preparedness to mitigate related supply chain disruption risks	(Meyer <i>et al.</i> , 2022)
Vendor Support	VS1	Vendors provide reliable after-sales service and technical assistance	(Naghshineh & Carvalho, 2022), (Chekurov <i>et al.</i> , 2021; Pakkala <i>et al.</i> , 2024)
	VS2	Long-term vendor partnerships are established for hardware and software maintenance	(Meyer <i>et al.</i> , 2020), (Jimo <i>et al.</i> , 2022)
	VS3	Vendor lock-in risks are assessed and mitigated through sourcing strategies	(Meyer <i>et al.</i> , 2020), (Gupta <i>et al.</i> , 2020)
Collaboration & Partnerships	CP1	Stakeholder collaboration in DSP ecosystem design and implementation	(Bharadwaj & Yeo, 2020; Stonig <i>et al.</i> , 2022), (Rocha <i>et al.</i> , 2021)
	CP2	Joint development of standardized practices and data-sharing mechanisms	(Tribello <i>et al.</i> , 2024), (Costabile <i>et al.</i> , 2022), (Kazantsev <i>et al.</i> , 2023)
	CP3	Engagement in cross-functional innovation and ecosystem standardization efforts	(Costabile <i>et al.</i> , 2022), (Metsä-Kortelainen <i>et al.</i> , 2020; Rocha <i>et al.</i> , 2021)

Table A2 Data Validation, Reliability, and CFA Estimates

Factor	Indicator Code	Correlation with Total	Cronbach's α	CR	AVE	CFA Standardized Parameter Estimates	CFA Parameter p-Value
Technological Compatibility	TC1	0.920034	0.966954	0.84307	0.64181	0.9394	<.0001
	TC2	0.930931				0.95436	<.0001
	TC3	0.935926				0.9632	<.0001
Material Availability & Performance	MP1	0.921218	0.962441	0.84978	0.65352	0.94846	<.0001
	MP2	0.920903				0.9468	<.0001
	MP3	0.916696				0.94323	<.0001
Infrastructure Requirements	IR1	0.91824	0.966553	0.86093	0.67373	0.93831	<.0001
	IR2	0.937299				0.96124	<.0001
	IR3	0.928985				0.95616	<.0001
Cost	C1	0.932853	0.972723	0.93522	0.82799	0.95084	<.0001
	C2	0.937744				0.95499	<.0001
	C3	0.951816				0.97564	<.0001
Scalability	S1	0.936019	0.969931	0.87422	0.69892	0.95664	<.0001
	S2	0.940277				0.96639	<.0001
	S3	0.929144				0.94593	<.0001
Quality Assurance	Q1	0.922908	0.963436	0.81979	0.6029	0.951	<.0001
	Q2	0.921109				0.9448	<.0001
	Q3	0.920875				0.94664	<.0001
Regulatory Compliance	RC1	0.927685	0.965045	0.85592	0.66446	0.95189	<.0001
	RC2	0.923433				0.94946	<.0001
	RC3	0.923719				0.94788	<.0001
Industry Readiness	IN1	0.936966	0.969053	0.9198	0.79268	0.9576	<.0001
	IN2	0.928629				0.95501	<.0001
	IN3	0.934047				0.95328	<.0001

Table A2 Data Validation, Reliability, and CFA Estimates (Cont'd)

Factor	Indicator Code	Correlation with Total	Cronbach's α	CR	AVE	CFA Standardized Parameter Estimates	CFA Parameter p-Value
Customization Needs	CN1	0.953662	0.978791	0.94595	0.85367	0.96917	<.0001
	CN2	0.955989				0.97241	<.0001
	CN3	0.95121				0.9654	<.0001
Sustainability	SCE1	0.928263	0.963986	0.84439	0.64399	0.95917	<.0001
	SCE2	0.909423				0.93152	<.0001
	SCE3	0.930522				0.95449	<.0001
Risk Management	RM1	0.926042	0.967434	0.88328	0.71614	0.94824	<.0001
	RM2	0.925713				0.94608	<.0001
	RM3	0.93786				0.96472	<.0001
Vendor Support	VS1	0.928173	0.963824	0.87703	0.70397	0.95742	<.0001
	VS2	0.917315				0.94009	<.0001
	VS3	0.921925				0.94647	<.0001
Collaboration & Partnerships	CP1	0.903844	0.95939	0.85689	0.66629	0.92917	<.0001
	CP2	0.922603				0.95419	<.0001
	CP3	0.913865				0.94282	<.0001

Table A3 SEM Path List

	Path		Standardized Estimate	Pr > t
TC	====>	TC1	0.94099	<.0001
TC	====>	TC2	0.95348	<.0001
TC	====>	TC3	0.96276	<.0001
MP	====>	MP1	0.94828	<.0001
MP	====>	MP2	0.9472	<.0001
MP	====>	MP3	0.94301	<.0001
IR	====>	IR1	0.93794	<.0001
IR	====>	IR2	0.96345	<.0001
IR	====>	IR3	0.95421	<.0001
C	====>	C1	0.95205	<.0001
C	====>	C2	0.95497	<.0001
C	====>	C3	0.97471	<.0001
S	====>	S1	0.95599	<.0001
S	====>	S2	0.9667	<.0001
S	====>	S3	0.94626	<.0001
Q	====>	Q1	0.95025	<.0001
Q	====>	Q2	0.94365	<.0001
Q	====>	Q3	0.94848	<.0001
RC	====>	RC1	0.95176	<.0001
RC	====>	RC2	0.94997	<.0001
RC	====>	RC3	0.94747	<.0001
IN	====>	IN1	0.95896	<.0001
IN	====>	IN2	0.95442	<.0001
IN	====>	IN3	0.95247	<.0001
CN	====>	CN1	0.96974	<.0001
CN	====>	CN2	0.9716	<.0001
CN	====>	CN3	0.96568	<.0001
SCE	====>	SCE1	0.9592	<.0001
SCE	====>	SCE2	0.93152	<.0001
SCE	====>	SCE3	0.95445	<.0001
RM	====>	RM1	0.94806	<.0001
RM	====>	RM2	0.94604	<.0001
RM	====>	RM3	0.9649	<.0001
VS	====>	VS1	0.96023	<.0001
VS	====>	VS2	0.93857	<.0001
VS	====>	VS3	0.94462	<.0001
CP	====>	CP1	0.92813	<.0001
CP	====>	CP2	0.95317	<.0001

Table A3 SEM Path List (Cont'd)

	Path		Standardized Estimate	Pr > t
CP	===>	CP3	0.94481	<.0001
TC	===>	Readiness	0.31287	<.0001
MP	===>	Readiness	-0.15459	0.0109
IR	===>	Readiness	0.30076	<.0001
C	===>	Readiness	0.35329	<.0001
S	===>	Readiness	-0.13809	0.0107
Q	===>	Readiness	0.32519	<.0001
RC	===>	Readiness	0.31156	<.0001
IN	===>	Readiness	-0.20426	0.0007
CN	===>	Readiness	0.41602	<.0001
SCE	===>	Readiness	-0.01395	0.8084
RM	===>	Readiness	-0.04547	0.414
VS	===>	Readiness	0.33143	<.0001
CP	===>	Readiness	0.21967	<.0001