AGILE PRODUCTION NETWORKS

AI AND WHOLEGARMENT® KNITTING FOR DECENTRALISED FASHION SYSTEMS

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Data Availability Statement: All relevant data are within the paper and its Supporting Information files.
Competing Interests: The Author(s) declare(s) no conflict of interest
DOI: 10.36253/fh-3692

Abstract

WHOLEGARMENT® knitting enables the production of complete, 3D seamless garments in a single automated process, offering highly programmable textile manufacturing. This practice-based research investigates the feasibility of a decentralised production model—the Future Factory Network (FFN)—using existing industrial 3D knitting infrastructure. Early-stage knit trials were conducted at production sites equipped with WHOLEGARMENT® systems, alongside hypothetical network modelling based on international trade data and offshore manufacturing data from an Australian apparel brand. A varied set of products was produced to examine system adaptability, reconfiguration time, and operational stability under decentralised conditions. The study focuses on operational performance, framing knitting machines as networked production nodes within a potential distributed manufacturing system. Findings suggest that WHOLEGARMENT® technology provides a viable foundation for low-waste, low-labour, just-in-time production when applied across multiple localised sites. The research situates WHOLEGARMENT® systems within an emerging AI-enabled manufacturing context, indicating how future integration could further enhance responsiveness and coordination across decentralised networks. This study contributes to ongoing discussions on hyperlocal production and digitally enabled manufacturing, proposing a structured pathway for reconfiguring fashion production toward modular, decentralised systems.

Keywords: *3D knit; Localism; Advanced manufacturing; Industry 5.0; Sustainability*

INTRODUCTION

Traditional offshore manufacturing systems have proven increasingly fragile in the face of geopolitical instability, pandemic-related disruption, and extreme climate events (Ivanov, 2023). At the same time, regulatory developments—such as the European Union's Ecodesign for Sustainable Products Regulation (ESPR) and the Digital Product Passport (DPP)—are placing new demands on fashion brands for supply chain transparency, traceability, and responsiveness (Quantis, 2018). Together, these pressures foreground a central challenge for the fashion industry: how to improve sustainability and production flexibility while relocating manufacturing closer to the point of demand.

Within this context, WHOLEGARMENT® knitting technology, developed by Shima Seiki, offers a distinct production paradigm. By producing complete, seamless garments in a single automated process, WHOLEGARMENT® systems reduce material waste and minimise reliance on post-production operations such as cutting, sewing, and linking (Choi, 2005; Pavko Čuden, 2022a). In contrast, fully-fashioned knitwear production depends on multiple labour-intensive post-knit stages, which introduce additional time dependencies and constrain responsiveness, particularly in on-demand or small-batch production settings (Larsson et al., 2012; Peterson et al., 2008).

Previous case-study research has demonstrated that on-demand WHOLEGAR-

MENT® production can support order-driven manufacturing without cutting or sewing, enabling relatively short fulfilment lead times in retail contexts (Peterson & Mattila, 2010). Such findings are particularly relevant given ongoing global shortages of skilled textile labour and the growing need to accommodate smaller, more diverse order volumes—conditions under which traditional assembly-based knit production models are increasingly difficult to sustain (Pavko Čuden, 2022a).

Building on this background, this research investigates the feasibility of utilising WHOLEGARMENT® knitwear technology within a distributed manufacturing network. The proposed Future Factory Network (FFN) model conceptualises a decentralised system of production hubs equipped with WHOLEGARMENT® machines, each capable of fulfilling orders locally while sharing digital infrastructure, programming logic, and material inputs. Rather than concentrating production in a single factory, the FFN model examines whether programmable knitting systems can be more efficient and responsive when dispersed across multiple sites.

The study is informed by theoretical frameworks on modular manufacturing platforms (Gawer & Cusumano, 2014) and digitally enabled local production ecosystems (Larsson, 2018), extending these perspectives through practice-based production trials and system-level analysis. The aim is not to evaluate knitwear aesthetics or design processes, but to assess whether WHOLEGARMENT® machines—already established in niche and design-led applications—can serve as the technical foundation for scalable, decentralised knitwear production.

Ultimately, this paper proposes that WHOLEGARMENT® knitting, supported by targeted automation and local infrastructure, presents a viable pathway toward more responsive, low-waste manufacturing systems. By shifting away from centralised, labour-intensive production models, programmable knit production offers the potential for improved resilience, traceability, and adaptability in fashion manufacturing, particularly in markets characterised by volatile demand and increasing regulations.

RECONFIGURING FASHION MANUFACTURING THROUGH PROGRAMMABLE TEXTILE SYSTEMS

The contemporary fashion industry is undergoing a transition from the long-established manufacturing models, which are increasingly challenged by geopolitical instability, environmental pressures, and market volatility. For decades, apparel production has been organised around large-scale, centralised offshore systems designed to maximise economies of scale (Pouillard & Dubé-Senécal, 2023). While effective under conditions of stable global trade, these models have proven vulnerable to disruption, including climate-related events, labour volatility, trade tensions, and the systemic impacts of pandemics (Ivanov, 2023). At the same time, rising expectations for traceability and verifiable data have exposed the limitations of supply chains reliant on geographically dispersed, opaque production processes (Abreu et al., 2012).

In parallel, shifts in consumer behaviour are reinforcing the need for alternative production approaches. Growing awareness of environmental impacts, alongside increasing demand for product customisation and rapid response cycles, has rendered traditional mass-production systems less competitive (Kozinets & Handelman, 2004). Shorter lead times and more adaptable product development structures are increasingly required, signalling a broader reconfiguration of the relationship between design, production, and market demand (Pucker, 2022).

Labour constraints further intensify these pressures. Global shortages of skilled textile workers—particularly in technically specialised and repetitive roles—with younger generations increasingly disengaging from manual textile labour (Pavko Čuden, 2022a; Stevick, 2023; Taylor & Townsend, 2014). Even in historically low-cost manufacturing regions, labour scarcity has eroded many of the economic advantages traditionally associated with offshore production. Against this backdrop, programmable and automated textile technologies have emerged as viable alternatives. Digitally controlled systems, exemplified by WHOLEGARMENT® knitting, significantly reduce reliance on manual assembly, minimise material waste, and support greater production agility through integrated, single-process garment construction (Cerulo et al., 2022; Larsson, 2018).

The adoption of such technologies enables a shift from centralised factory models to distributed, and in some cases hyperlocal, production structures. By relocating manufacturing closer to the point of consumption and leveraging automation to reduce labour dependency, these networked models offer improved resilience, operational transparency, and reduced environmental impacts—particularly in relation to transport emissions and material handling (Ivanov, 2023). Rather than representing incremental technical upgrades, programmable textile systems facilitate a systemic reorganisation of fashion manufacturing, reshaping how production capacity, responsiveness, and sustainability are configured within contemporary constraints.

Taken together, regulatory pressures, evolving consumer expectations, labour shortages, and advances in digital manufacturing converge to signal a decisive shift in the global fashion production landscape. The proposed network is characterised by agility, digital integration, and sustainability, positioning programmable textile technologies as a critical foundation for more interconnected, adaptive, and future-oriented manufacturing networks.

DISTRIBUTED AND HYPERLOCAL MANUFACTURING NETWORKS

Distributed and hyperlocal manufacturing models have emerged as potential responses to contemporary challenges in manufacturing and supply chain management. Distributed manufacturing refers to decentralised production organised through networks of smaller, geographically dispersed units, often located closer to points of demand (Gawer & Cusumano, 2014). Hyperlocal manufacturing represents a more specific configuration within this broader category, in which production occurs within a narrowly defined geographic area, enabling rapid and flexible responses to local or regional needs (Langvik, 2022).

These networked production models offer several advantages over traditional centralised systems, including improved resilience to disruption, reduced transportation impacts, and greater responsiveness to fluctuating consumer demand (Ivanov, 2023). In the context of textile and knitwear manufacturing, the application of 3D knit technologies within distributed and hyperlocal frameworks presents a further opportunity to reduce material waste and supply chain emissions while supporting smaller batch sizes and variable production volumes (Cerulo et al., 2022; Larsson, 2018). Such models are developing in response to mounting pressure on global supply chains and increasing demand for adaptable, locally responsive manufacturing systems.

The shift toward distributed manufacturing represents a structural departure from industrial models historically organised around economies of scale. Instead, networked production structures prioritise economies of scope and adaptability, enabling rapid reconfiguration of production flows and closer alignment with market demand (Gawer & Cusumano, 2014). Advanced digital fabrication technologies play a central role in this transition, supporting flexible production, reduced waste, and improved coordination across dispersed manufacturing sites (Cerulo et al., 2022; Larsson, 2018). As Pavko Čuden (2022) notes, traditional textile manufacturing has long relied on centralised facilities, extended supply chains, and large-scale volume production. These arrangements are increasingly problematic in relation to environmental sustainability, transparency, and responsiveness to volatile consumer demand (Quantis, 2018). Distributed production offers an alternative approach, using strategically located smaller facilities to manufacture garments closer to the point of use, thereby reducing transport-related emissions and supporting just-in-time production models that minimise excess inventory and material waste (Larsson, 2018; Swanson & Lankford, 1998).

However, implementing distributed manufacturing in textile production requires more than geographic dispersion alone. Effective coordination across multiple production sites depends on digitally enabled infrastructure, logistics, and process integration (Ivanov et al., 2016). Industry 4.0 technologies—including the Internet of Things (IoT), cloud computing, and data analytics—enable real-time communication, monitoring, and coordination across distributed networks, supporting production efficiency, material traceability, and reduced downtime in decentralised environments (Frank et al., 2019; Simonis et al., 2016).

Hyperlocal manufacturing represents a more constrained form of distributed production, though not all distributed systems operate at a hyperlocal scale (Srai et al., 2016). In textile manufacturing, small-scale urban and regional facilities—including microfactories—are increasingly adopting WHOLEGARMENT® 3D knitting technology. These sites can produce a diverse range of knit products with minimal machine reconfiguration, enabling production closer to the point of consumption and aligning with just-in-time manufacturing principles.

By embedding circular economy principles within local production ecosystems, hyperlocal models extend the benefits of distributed manufacturing further (Langvik, 2022). Advances in knitting technology—particularly seamless construction and digitally driven workflows—have created new conditions for integrating sustainability, responsiveness, and low-waste outputs into production systems. Within this context, hyperlocal knit manufacturing offers an alternative to high-volume models dependent on specialised labour and extended lead times, supporting scalable production with fewer logistical constraints and reduced material waste (Pavko Čuden, 2022b). Taken together, distributed and hyperlocal manufacturing networks represent both a relocation of production and a reorganisation of manufacturing logic within the fashion industry. By leveraging advanced digital technologies and intelligent management systems, these networked models provide a viable pathway toward more resilient, transparent, and responsive production systems capable of addressing contemporary economic, environmental, and logistical challenges (Ivanov, 2023).

AI-ENHANCED KNITWEAR PRODUCTION

Artificial intelligence (AI) is increasingly recognised as a transformative component of advanced manufacturing, with growing relevance for knitwear production systems. Broadly defined, AI encompasses computational systems capable of tasks associated with human cognition—such as pattern recognition, prediction, and optimisation—through learning from data inputs and prior outcomes (Hassani et al., 2020). Within textile manufacturing, AI applications have been explored across operational efficiency, predictive modelling, design support, and sustainability-related decision-making.

In knitwear production, AI has been shown to support efficiency gains through predictive analytics and parameter optimisation. Developments in machine learning (ML) enable data-driven modelling that can reduce reliance on physical sampling by predicting fabric behaviour and performance prior to production. This approach has the potential to shorten development cycles, reduce material waste, and improve alignment between design intent and manufacturing outcomes. Experimental studies using artificial neural networks (ANNs) have demonstrated the ability to predict mechanical and sensory properties of knitted fabrics—such as drape, elasticity, and tensile behaviour—based on yarn type, stitch configuration, gauge, and machine parameters (Singha et al., 2022). While these studies are dataset-based rather than industrially deployed, they provide a foundation for understanding how AI could support future knitwear optimisation.

These capabilities are particularly relevant to WHOLEGARMENT® systems, given their fully programmable structure and reliance on digital knitting instructions rather than manual assembly. The elimination of cutting, sewing, and linking enables a tightly controlled production environment in which machine parameters, material inputs, and structural variables are digitally defined, creating conditions well suited to AI-assisted analysis and optimisation (Pavko Čuden, 2022b).

One of the most immediate and practical applications of AI within knitwear manufacturing is predictive maintenance. When integrated with sensor systems and Internet of Things (IoT) infrastructure, AI-enabled monitoring tools can detect deviations in machine behaviour and identify maintenance requirements before failures occur (Ivanov et al., 2016; Simonis et al., 2016). This capability is particularly significant in decentralised and hyperlocal production networks, where technical staff may not be continuously present on site, and machine downtime directly affects production continuity across multiple nodes. Ensuring machine uptime is therefore critical to the viability of distributed manufacturing models, and AI-supported maintenance offers a means of stabilising production across geographically dispersed facilities.

Beyond maintenance, AI has potential applications in real-time process optimisation within WHOLEGARMENT® knitting systems. Prior research suggests that AI-assisted adjustment of parameters such as yarn tension, loop size, and stitch density could improve material efficiency, fabric consistency, and production speed, while reducing waste through more precise control of yarn utilisation (Cerulo et al., 2022; Scheidt et al., 2020). In this research, such applications are framed as prospective capabilities rather than validated outcomes.

AI-driven design and pattern generation also represent a promising area of integration. Intelligent systems capable of generating or adapting knitting patterns based on defined constraints—such as performance requirements or sustainability objectives—have been proposed to reduce the technical complexity traditionally associated with knit programming (Scheidt et al., 2020). Techniques such as long short-term memory (LSTM) neural networks have demonstrated potential in modelling sequential stitch relationships and generating knit structures, potentially reducing the translation gap between design intent and machine programming (Eckert, 1999). In hyperlocal production contexts, where adaptability and rapid iteration are critical, such tools could enable faster development cycles with reduced reliance on highly specialised programming expertise.

In addition, AI-enabled data tracking supports the traceability and transparency requirements of emerging regulatory frameworks, including the Digital Product Passport. By recording material usage, production parameters, and process data throughout the manufacturing lifecycle, AI systems can contribute to greater accountability and alignment with sustainability and circular-economy objectives (Pavko Čuden, 2022b; Quantis, 2018).

Despite these opportunities, significant barriers to AI adoption remain. Effective implementation requires access to high-quality data, reliable predictive models, and appropriate digital infrastructure, alongside the expertise needed to interpret and manage AI outputs (Singha et al., 2022). These challenges are particularly pronounced for smaller manufacturers and geographically isolated production sites. However, as AI tools mature and become more accessible through cloud-based platforms and open-source frameworks, these constraints may lessen, enabling broader adoption across diverse manufacturing contexts.

In summary, while AI was not implemented within the applied trials of this research, existing research outcomes and modelling-based studies indicate a clear role for its strategic integration in future knitwear production systems. When aligned with programmable technologies such as WHOLEGARMENT® knitting, AI offers a pathway toward more efficient, adaptable, and sustainable manufacturing—particularly within decentralised and hyperlocal production networks where responsiveness and resource efficiency are critical.

METHODOLOGY

This research employs a practice-based methodology to evaluate the feasibility of deploying WHOLEGARMENT® knitting technology within a hyperlocal, distributed 3D knit manufacturing framework. While the initial research design considered the integration of artificial intelligence (AI), AI tools were not implemented due to resource constraints. Instead, the study examines the operational performance of programmable knit technologies across decentralised production settings and evaluates the resilience of a simulated Future Factory Network (FFN). Analysis focuses on system adaptability, production responsiveness, and logistical viability, excluding aesthetic or stylistic outcomes.

As the second phase of a broader doctoral investigation, this stage builds on earlier conceptual work through applied experimentation and data modelling. Trials were conducted across two urban manufacturing sites—University of Technology Sydney (UTS) and Knovus in Melbourne—both equipped with WHOLEGARMENT® machines, including the Shima Seiki SWG-XR, MACH2XS, and MACH2VS. Each site operated as a production node within the simulated FFN, enabling testing of decentralised manufacturing portability.

A diverse range of products—including garments, blankets, and technical items such as ankle supports—was produced to assess system flexibility under variable, real-world production conditions. Trials comprised single-product runs to establish baseline efficiency, alternating-product runs to examine reconfiguration time and responsiveness, and integrated batch sequences to simulate continuous, demand-driven production. Operational data collected during the trials included machine setup and programming time, digital file transfer and adjustment durations, knitting time, product changeover downtime, yarn consumption, fabric weight, and post-production quality observations. Production time definitions were informed by prior simulation-based modelling of knit-on-demand WHOLEGARMENT® systems, which reported preparation times of approximately 11.5 minutes per order and total lead times of 165.5–187.5 minutes (Peterson et al., 2008). Knitting duration was modelled within a 35–70-minute range, with a typical value of 55 minutes, to reflect normal operational variation, such as yarn breaks or minor machine interruptions. Quantitative analysis focused on production efficiency, machine uptime, throughput, and flexibility, assessed through setup duration and ease of transition between product types. Sustainability was examined through material efficiency, waste generation, and energy use, while operational stability was evaluated via downtime logs, maintenance events, and recorded fault occurrences. Qualitative observations complemented this analysis by documenting workflow patterns, operator interaction, and procedural friction points.

The FFN was further examined using spatial modelling of a hypothetical distributed production nodes approach developed within a digital design environment. The models represent production as a network of geographically distributed sites connected through transport relationships, enabling comparison between centralised and decentralised manufacturing configurations. A reference scenario informed by international knitwear trade data was used to characterise conventional offshore production, against which a distributed, locally oriented network was conceptually compared.

Modelling was used as an exploratory tool rather than a predictive one, supporting comparative discussion across broad performance dimensions including time, distance, resource use, and capacity. In this way, the approach provides a structured means of examining the potential characteristics of hyperlocal production networks—such as adaptability and resilience—without specifying technical or operational parameters reserved for later publication.

The findings from this phase provide practice-based evidence supporting the viability of integrating WHOLEGARMENT® knitting within decentralised production models. While not presented as a comprehensive solution to broader industry challenges, the framework demonstrates how programmable knitting systems may support more responsive, localised, and resource-efficient manufacturing, establishing a foundation for future AI-enabled system development.

DISCUSSION

This study evaluated decentralised knit production using WHOLEGARMENT® technology within a simulated Future Factory Network (FFN). While artificial intelligence (AI) was not implemented in the applied trials, empirical and modelling-based evidence from the literature highlights its potential role in optimising future decentralised knitwear systems.

Prior simulation studies of knit-on-demand WHOLEGARMENT® production provide a useful benchmark for interpreting the operational performance observed in this research. Peterson et al. (2008) report preparation times of approximately 11.5 minutes per order and total customer fulfilment times ranging from 120 to 301 minutes, with mean values of 191 minutes for wool and 206 minutes for cotton garments. Knitting duration in these simulations was modelled using a triangular distribution of 35–70 minutes, with a modal value of 55 minutes, explicitly accounting for operational variability such as yarn breaks and minor machine interruptions. Machine utilisation across fifteen simulations ranged from 79.1% to 90%, with an average of 86%, indicating relatively high and stable equipment use within a knit-on-demand context. These results reinforce the importance of accounting for interruptions, setup time, and utilisation when assessing decentralised production performance.

Within the FFN context tested in this study, such findings underscore why predictive maintenance represents one of the most immediate opportunities for AI-supported optimisation. As demonstrated in Industry 4.0 research by Ivanov et al. (2016) and Simonis et al. (2016), sensor-driven monitoring systems can identify changes in machine behaviour before faults occur, reducing unplanned downtime. This capability is particularly relevant for decentralised and hyperlocal manufacturing environments, where technical staff are not always on site, and machine downtime directly affects production continuity across multiple small nodes.

Beyond maintenance, AI has demonstrated potential to improve programming efficiency, optimise parameters, and predict fabric properties in knitwear production. Experimental modelling studies using artificial neural networks (ANNs) have shown that fabric mechanical behaviour can be predicted based on stitch type, yarn characteristics, and gauge parameters (Singha et al., 2022).

While these studies were conducted on experimental datasets rather than deployed industrial systems, they provide evidence that AI tools could reduce reliance on physical sampling and manual parameter adjustment in future implementations of the FFN. In this research, such capabilities are positioned as prospective enablers rather than validated outcomes.

The suitability of WHOLEGARMENT® systems for AI integration is further reinforced by their high level of programmability and digital precision. Review-based research with strong industrial grounding documents that WHOLEGARMENT® technology eliminates linking and assembly processes, reduces dependence on scarce skilled labour, and supports small-batch, variable production (Pavko Čuden, 2022b, 2022a). Linking, in particular, is identified as a persistent bottleneck in fully fashioned knitwear production, both due to its labour-intensive nature and the declining availability of skilled operators. These documented industry constraints help explain why programmable, single-process production systems are structurally better suited to decentralised and hyperlocal manufacturing models.

Simulation-based studies further suggest that digital interfaces and automation can significantly influence output capacity in customised knitwear environments. Peterson et al. (2011) demonstrated that order-made WHOLEGARMENT® systems supported higher volumes of customised products over equivalent simulation periods compared to manual co-design processes, particularly when configuration interfaces replaced reliance on sales staff. Total co-design time was reduced from an average of 57.5 minutes in manual processes to 39.5 minutes in digital WHOLEGARMENT®-based configurations, while overall production output increased when additional configurators were introduced. Although these findings are simulation-based, they provide insight into how interface design and automation choices may affect scalability within distributed production networks.

From a workforce perspective, the integration of AI should not be framed as a threat to employment but as a response to structural challenges facing the textile industry. As Pavko Čuden (2022a) notes, younger generations are increasingly disengaging from repetitive, labour-intensive textile roles, contributing to skills shortages that constrain production capacity. AI-assisted systems have the potential to lower technical barriers, enabling smaller teams to operate complex production equipment with greater confidence and consistency. Within a hyperlocal manufacturing context, this may also support the re-emergence of textile production in regions where traditional skill bases are no longer available.

However, the implementation of AI within decentralised knitwear networks remains constrained by data availability, interoperability between production nodes, and the need for domain-specific expertise to interpret and act on algorithmic outputs.

In summary, while AI was not implemented in the applied trials of this research, existing empirical and modelling-based studies indicate a clear role for its strategic integration in future iterations of decentralised knitwear manufacturing systems. As the FFN model develops, AI is likely to function as a critical enabler—supporting machine reliability, production responsiveness, and resource efficiency—while reinforcing the broader shift toward localised, flexible, and digitally coordinated manufacturing networks.

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