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Review

Improving the enterprise performance: An empirical analysis of digital supply chain transformation in Guangxi manufacturing industry

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Abstract: This study investigates how digital supply chain transformation affects enterprise performance in Guangxi's manufacturing sector, with a focus on Electric Vehicle (EV) enterprises. Utilizing the quantitative research approach, data was collected through a questionnaire survey from 197 respondents including the manufacturers, distributors, and suppliers of the Guangxi Electric Vehicle Manufacturing Industry. To test the reliability, correlation, regression, and discriminant validity assessments the structural equation modeling is used by applying the SmartPLS 3.0. The results revealed that there is a strong correlation between agile capability, digital transformation, innovation capability, and enterprise performance. All the structured hypotheses tested significantly positive, though, digital supply chain transformation positively influences enterprise performance in Guangxi's manufacturing industry, emphasizing the importance of agile capability, digital transformation, and innovation capability. This study highlights the importance of digital supply chain transformation in improving business performance in the Guangxi manufacturing sector. It serves as a guide for policy decision-makers and investors while they are planning their future investments, especially on issues about the optimization of supply chain operations.

Keywords: enterprise performance; electric vehicle enterprises; digital supply chain transformation; agile capability; innovation capability

1. Introduction

In the automobile industry, China takes pride in being a major manufacturing economy with remarkable accomplishments in various industrial sectors. In 2010, China became the largest producer of cars in the world by surpassing America and thus marking its rise to become the leading global force in the production and sales of automobiles. This transition shows that China is moving closer to becoming a global leader when it comes to car sales (C. Liu et al., 2021; X. Liu, 2020).

Considering the sustainability aspect, the Chinese government has given full support to new energy vehicles and it is encouraging electric car manufacturers to scale up their production (Li, 2017; Nazeer et al., 2020). At present, new energy vehicles in China's automobile market include HEV (hybrid electric vehicle), BEV which refers to battery electric vehicles including solar cars, FCEV which are fuel cell electric vehicles and other advanced technologies with supercapacitors and flywheels (Zheng, 2019). This development is important for creating a clean and green environment and China included electric vehicle growth and development in the agenda of its twelfth Five-Year Plan for, the first time in 2010 (Y. Liu, 2022). During the 13th Five-Year-Plan in 2016, the government of China issued an agenda for the National Strategic Emerging Industries which also included the development of new energy vehicles. Simultaneously during its recent Five-Year Plan established in 2022 the Government of China has set a target that by 2025 will convert at least 20% of its vehicles to new or green energy which mainly include electric vehicles (Tan et al., 2023). This overall development shows the keen commitment of the Government of China to the promotion of electric vehicles.

In China, the main Electric Vehicle (EV) production plants are based in Guangxi province, though Guangxi is known as the hub of EV production. In the 2016 "Five-Year Plan", Guangxi decided to increase EV production, and several measures were taken to promote the high-quality development of the electric vehicles industry (Zhang et al., 2018). Infect Guangxi's new energy automobile industry started from zero, and during the "13th Five-Year Plan" period, the cumulative output of electric vehicles reached up to 316,000 (Wu and Zhang, 2021). The "Fourteenth Five-Year Plan for the Development of Guangxi's New Energy Automobile Industry" outlines ambitious goals for the region. Guangxi has set a target to become the domestic central hub for new energy vehicles in 2025, referred to as "the three bases." Based on the Liuzhou automobile industrial cluster, Guangxi plans to pull other cities to develop new energy vehicles, promote scientific and technological innovation, and upgrade the modernization level of the local new energy vehicle industry chain (Zuo, 2020). A strong technological innovation system is required and deemed necessary for this ambitious growth target (Zhao, 2018).

The current challenges being faced by the Guangxi EV industry are the lack of supporting facilities for electric vehicles, and the process of infrastructure construction which is slow (Geng et al., 2017). This basic supporting facilities infrastructure includes such as electric vehicle battery exchange stations and battery charging stations development which are still relatively slow, the penetration rate is not high enough, and the outreach is very limited (Zhang, 2023). One of the other problems is the inconsistent standards of charging stations and charging pile equipment at various places, which are deemed necessary to be standardized and the whole research and development shall be streamed out in the same direction (Li, 2022). Supply chain management is also one of the major actors in EV production which comprises more than 50% of the total production cost (Awan and Shafiq, 2015; Degraeve and Roodhooft, 1999). Electric Vehicle manufacturing Supply Chain Management (SCM) deals with the organization and control of all activities relating to material procurement, production, and distribution in EVs. This includes getting lithium, cobalt, and rare earth metals they need for batteries and electric motors from ethical and sustainable sources. SCM also facilitates the efficient assembly of battery cells and packs; integration of advanced power electronics and software systems as well as traditional automotive parts with specialized EV components. Additionally, SCM in the context of EV manufacturing tackles issues like the logistics problem of raw materials transportation to plants and delivering completed cars to retail outlets while decreasing the carbon footprint within stringent environmental regulations (Piprani et al., 2024).

For the above reason, effective SCM in this domain involves robust quality assurance practices; strategic supplier alliances; and innovation via technology focus on sustainability aimed at cost management while ensuring the reliability and performance of EVs. Competitiveness cannot be achieved without innovation in supply chain management, this innovation could include digitalization which is crucial to adhere to the advancement imperative of Guangxi EV growth. In short, the development of the new energy automobile industry still requires enterprises to improve the ability of independent research and development and independent innovation, constantly improve all aspects of electric vehicles, and promote the upgrading of the new energy industry, to stimulate the economic growth of Guangxi and achieve a win-win situation between the government and enterprises (Lin, 2021).

Today's business environment is highly dynamic with companies facing tough competition and always striving to improve their performance (Naz et al., 2018; Qin, 2019; Yaqub et al., 2018). The Guangxi manufacturing sector experiences the challenges of global markets and technological development and, therefore, must engage in digital supply chain transformation. This can have a major impact on enterprise performance since it could change traditional operational paradigms, streamline processes, increase resource efficiency, and drive growth as well as sustainability (Batool et al., 2019). Due to the rapid rate at which digitalization is taking place in the context of the Guangxi manufacturing industry, it is important to conduct comprehensive research on the impacts of digital supply chain transformation. By so doing, this kind of research helps organizations that want to stay competitive in an increasingly digitized world comprehend both sides of the coin when it comes to this transformation (Rehman and Shafiq, 2019; Xue, 2022).

Consequently, the purpose of this research is to evaluate the probable outcomes of digital supply chain transformation on enhancing corporate performance in EV manufacturing in Guangxi. In particular, it looks at how improvements in digital technologies can enhance operational effectiveness, minimize costs, and make companies more competitive within this sphere. This study investigates what motivates firms' green innovation adoption in their manufacturing supply chains and incorporates outsiders, insiders, and systemic factors as well as collaborative innovation under a unique theoretical framework that will guide the implementation of green innovation within the supply chain by Chinese EV manufacturers.

2. Literature review

According to the study theme and purpose, this study reviews the literature on digital transformation, supply chain, and enterprise performance.

Performance is a term used to describe the measurable outcomes that signify how well an organization is achieving its goals. In particular, enterprise performance denotes various measures such as operational efficiency, financial results, market competitiveness, and innovation capabilities in the manufacturing industry (Lu et al., 2023). Performance in the manufacturing industries is not about money alone but also about productivity levels, quality of goods produced, customer satisfaction as well as adapting and innovating to changes in market conditions. These performance metrics can be significantly affected by digital supply chain transformation through leveraging advanced technologies like big data analytics, IoT, and cloud computing for enhancing supply chain visibility, optimizing logistics, and streamlining operations. They include shorter response times to market needs, reduced production costs, and better coordination throughout the whole supply chain through the digitizing of processes along it. Greater changes made across a range of performance indicators result in an improved company's overall performance leading to maintaining a competitive advantage for manufacturing firms within Guangxi from a global market which continues to change rapidly (Okoye et al., 2024).

2.1. Digitization and how it impacts enterprise performance

Digital transformation is a kind of organizational strategic behavior, and it is a kind of change behavior in that organizations use digital technology to transform the organizational structure and service model of enterprises (Hanelt et al., 2021). Through the reform of business models, digital transformation will eventually have an impact on various corporate performance, such as marketing, financial, and innovation performance (W. C. Watanabe et al., 2024). More studies believe that digital transformation can help enterprises realize data-driven operation management processes, improve decision-making efficiency, reduce production and operation costs, increase operating profits, and ultimately improve the market performance of enterprises (Tseng et al., 2021).

In today's unfavorable business environment that has turned out to be highly competitive and unstable, these industries such as the manufacturing industry must continue converting all their activities into digital forms so that they may keep on living (Krasnikov and Jayachandran, 2008). Internet clothing manufacturers are a good example of how digital transformation can change manufacturing (Watanabe and Shafiq, 2023). They include big data in the product development process which makes all stages of research and development work more effective. This way, they join forces of people and information within the R&D activity enhancing its quality (Braganza et al., 2017), therefore, transforming the internet clothing manufacturing industry or increasing the market performance of firms. Through digitalization and big data analysis, the redesigning of corporate business models has cut down the response time to market demand as well as improved efficiency in operational processes (Guo et al., 2020), and also enhanced the market competitiveness and performance of enterprises.

Based on the above analysis, this study proposes hypothesis H1 for the digital transformation of EV manufacturing enterprises working in Guangxi, China.

- H1: Digital transformation has a positive impact on manufacturing enterprise performance.

2.2. Digital transformation and organizational agility

The theory of dynamic capability points out that dynamic capability is the abstract ability to reconstruct and make full use of internal and external resources for perception and rapid response (Ambrosini and Bowman, 2009; Mushir and Shafiq, 2024; Rahmani et al., 2024). Organizational agile capability is a specific dynamic capability, characterized by rapid perception and quick response. Through rapid response to market demand and restructuring of enterprise resources, organizations prosper and grow (Walter, 2021; W. Watanabe et al., 2024).

Digital transformation can help manufacturing companies e.g. EV enterprises to adapt to a dynamic and changing environment by enhancing organizational agility. Big data analysis ability can deeply analyze and obtain market demand, improve the information sharing level of supply chain, make supply chain information more transparent and visible, reduce the negative impact caused by demand distortion, and facilitate manufacturing enterprises to dynamically obtain key information of customer demand to make precise decisions, which is the guarantee for the improvement of market response agility (Huang et al., 2021; Shafiq et al., 2023). Modular information system design is adopted to achieve efficient production through the reconfiguration of enterprise resource modules, and the agile capability of the production process is improved (Mathrani, 2022). Moreover, companies with great IT capabilities and active investment orientation towards IT have strong digital platform utilization capabilities as well as data utilization awareness which also form a basis for enhancing agile capabilities (Nazeer and Fuggate, 2019; Noceti, 2020). This study divides agile ability into two dimensions: market response agility ability and operation adjustment agility ability. Market response agility enables enterprises to quickly capture changes in market demand by monitoring the external market, and then improve products and services to meet customers' personalized needs (Smith, 2007). This capability involves the development, marketing, and other departments of enterprises.

Studies have shown that digital transformation has a significant effect on market response agility. Through investigation found that the active application of information network technology can enable manufacturing enterprises to accurately grasp the market price threshold fluctuations and other information, to help them timely adjust the structure of manufactured products and improve the market response agility (Tao et al., 2018). De Diego Ruiz et al. (2023) used the method of fuzzy set qualitative comparative analysis to find that the dynamic capability enabled by IT can promote the market response agility and operational adjustment agility of manufacturing enterprises. The agile capacity of operational adaptation is the ability of a firm to adjust internal operating links in response to shifts in market demand. This capability mainly concerns internal business process reconfigurations that mainly involve production, operations, and management in administration for the organization (Forkmann et al., 2017). As another important agile capability, digital transformation also has a positive impact on its formation (Centobelli et al., 2020). Tallon's study found that IT capability promoted business process agile capability. After further study, IT was found that IT management capability promoted business process agile capability more in turbulent environments, while IT technical capability promoted business process agile capability more in stable environments (Chen et al., 2014).

Based on the above analysis, this study believes that digital transformation can promote the development of market response agility and operational adjustment agility, and proposes the hypothesis for EV manufacturing enterprises as follows.

- H2: Digital transformation has a positive impact on organizational agility.

2.3. Digital transformation and dual innovation ability

Dual innovation ability refers to the ability of an enterprise to balance exploration and utilization of activities when facing a dynamic and complex external environment, and achieving a balance between the two is a sign of the realization of ambidexterity (Zhang et al., 2023). From the perspective of dynamic capability theory, the realization of organizational dual capabilities requires not only the ability to perceive opportunities and reconstruct resources to promote exploration capabilities, but also the ability to acquire opportunities and integrate resources to promote utilization capabilities, and the combination of the two can achieve a balance between utilization and exploration activities (Lichtenthaler and Lichtenthaler, 2009). The digital technology and application technology capabilities involved in the process of digital transformation can promote the establishment of enterprise dual capabilities from the perspective of dynamic capabilities (Shafiq et al., 2021; Teece, 2014). Employees can learn on this digital virtual platform, thereby cultivating their open attitude towards new opportunities (Valk and Planojevic, 2021), which is the key to exploration activities. The same is true of the mechanism of the human resource management system for the improvement of dual capabilities, which can integrate organizational, social, and human resource capital to balance exploration and utilization activities (Ragmoun and Alwehabie, 2020). The research proves that the structural and psychological empowers in digital empowers eliminate the structural barriers for enterprises to obtain information resources, and enhance the autonomy consciousness of employees, which is conducive to the enterprises removing the obstacles in perceiving and obtaining resources, and further improving the dual ability (Qiu et al., 2020).

From the perspective of exploration ability and utilization ability alone, the introduction of new information technology is itself a kind of enterprise exploration behavior, and advanced information technology can promote knowledge transfer, explore new organizational processes, and enhance exploration ability (Shafiq et al., 2021). In turn, IT process innovation can promote enterprises to continuously use the existing unique knowledge and resources to improve products, thus strengthening the utilization ability (Yu et al., 2017). Park et al. ‘s research proves that IT expenditure, IT training, and intensive use of IT for digital transformation improve exploration and utilization ability: IT expenditure means that enterprises introduce more resources, enable enterprises to use new information systems, and lay a foundation for the improvement of enterprise exploration ability. IT training enhances the business skills of IT staff and business staff, promotes the use of existing information systems, better understanding of domain knowledge, and improves the utilization ability of enterprises; The increase in IT usage intensity represents the success of the new IT implementation, which is an important aspect of digitization and will directly affect the utilization and exploration ability (Ritter and Pedersen, 2020). It can be seen that digital transformation is likely to promote the formation of dual capabilities. To keep in view the above discussion it is imperative to explore the impact of digital transformation on innovation capability and we have proposed the hypothesis regarding this investigation as listed below.

- H3: Digital transformation has a positive impact on organizational innovation capability.

2.4. Organizational agility and enterprise performance

Enterprise performance is an indicator to measure the achievement of an enterprise’s development goals and it represents the final result of their operation.

Perception, learning, coordination, integration, and innovation are the main ways through which dynamic capabilities impact a firm's performance (Ferreira et al., 2020; Kiani et al., 2020). As far as manufacturing firms are concerned agile capability acts as a unique dynamic capability that enhances their performance. For manufacturing firms efficient production and stability in supply chains are the most important things for success (Dar et al., 2021). By rearranging organizational resources, agile capabilities can help manufacturers respond faster to changing markets thereby allowing them to produce more efficiently while also mitigating risks of supply chain disruptions (Akhtar et al., 2020; Gunasekaran et al., 2019; Lu et al., 2023).

Organizational agility can be divided into market response agility and operational adjustment agility, both of which may have an impact on the performance of manufacturing enterprises (Nafei, 2016). Market response agility under uncertain environmental conditions usually improves the competitive performance of enterprises by quickly capturing changes in market conditions, improving the speed of product customization, and shortening the reaction time (Ahammad et al., 2021). When assessing the impact of IT capabilities on organizational agility and corporate performance, Chakravarty et al. (2013) found that the market response agility of an enterprise that can anticipate market changes and make use of opportunities and challenges can significantly improve its performance. Strong operational adjustment agility can help enterprises reduce operating costs, mainly by building new partnerships, improving operational flexibility, and reconstructing resources. Through this capability, the customer retention rate can be improved, thus improving corporate performance (Chakravarty et al., 2013; Tashfeen et al., 2023). Research shows that business process agility enables companies to easily and quickly reorganize business processes to adapt to the constant changes in the market environment, thus achieving excellent financial performance (Arteta and Giachetti, 2004). To investigate its impacts on enterprise performance the following hypothesis has been framed.

- H4: Organizational agility positively affects the manufacturing enterprise performance.

2.5. Organizational dual competence and enterprise performance

Most existing studies agree that organizational dual capability is a kind of dynamic capability, that is conducive to the establishment of long-term competitive advantages of organizations, and this advantage is mainly achieved by improving the innovation and changeability of enterprises (Sugarman, 2014; Zahra et al., 2006). Manufacturing enterprises with dual capabilities are superior to those without in terms of innovation capability (Rahmani et al., 2024). This innovation capability improves the development performance of new products and thus enhances the market competitiveness of enterprises' products (Xu et al., 2023). To maintain competitive advantages, manufacturing enterprises establish a business model imitation isolation mechanism, which will also be better consolidated due to the combination of dual innovation ability and business model, thus greatly reducing the probability of successful model imitation, consolidating the market dominance of manufacturing enterprises and improving their market competitiveness (Aljanabi, 2022).

At the same time, in the context of technological innovation of enterprises, the sales level represents the level of market competitiveness of enterprises to a certain extent, and research has proved that the product sales level of manufacturing enterprises is positively affected by utilization and exploration activities (Buckley et al., 1988; Chen et al., 2024). In addition, when an enterprise adopts a proactive development strategy in the context of environmental volatility, the positive impact of dual capabilities on enterprise competitiveness and financial performance is particularly significant, and enterprises that can balance exploration and utilization activities tend to obtain higher market competitiveness (Li et al., 2021). The impact of innovative ability in terms of the manufacturing enterprises' performance is given below.

- H5: Organizational innovation ability positively affects the manufacturing enterprise performance.

2.6. Research gap

Despite extensive research on the impact of digital transformation on enterprise performance, organizational agility, and innovation capability, there is a notable lack of empirical studies specifically focusing on the Electric Vehicle (EV) manufacturing industry within Guangxi, China. While existing literature broadly covers various industries and geographic regions, the unique context of Guangxi's EV manufacturing industry (C. Liu et al., 2021; Li, 2017; Wu and Zhang, 2021; Y. Liu, 2020; Zheng, 2019; Zuo, 2020), particularly regarding its adoption and implementation of digital supply chain practices, remains underexplored. Additionally, the interplay between digital transformation, organizational agility, and dual innovation capabilities in this specific regional industry context needs further investigation. This gap presents an opportunity to provide localized insights and practical implications for EV manufacturing enterprises in Guangxi, contributing to the broader discourse on digital transformation in the EV manufacturing sector.

2.7. Research framework

Through a literature review, this study summarizes the development of Guangxi's electric vehicle industry from the perspective of consumers and enterprise development. According to the development status of Guangxi's electric vehicle manufacturing industry and the government's policy support for the electric vehicle industry, Guangxi's electric vehicle manufacturing industry has undergone different degrees of digital transformation and has achieved good development. Guangxi's electric vehicle output has jumped to the forefront of the country.

It has been shown by many scholars that digital transformation brings about a meaningful positive impact on business outcomes (Gao et al., 2023; Peng and Tao, 2022; Wang et al., 2024) and also enhances the agility, innovativeness as well as entrepreneurial capabilities of an enterprise. This means that the agile ability, entrepreneurship, and innovation capacity of a firm may have implications for corporate performance (Kashif et al., 2020). Thus, this research will seek to find out whether digital transformation is significantly related to agile ability, innovation capacity, and overall business performance among EV firms, which have not been investigated previously. **Figure 1** shows the research framework.

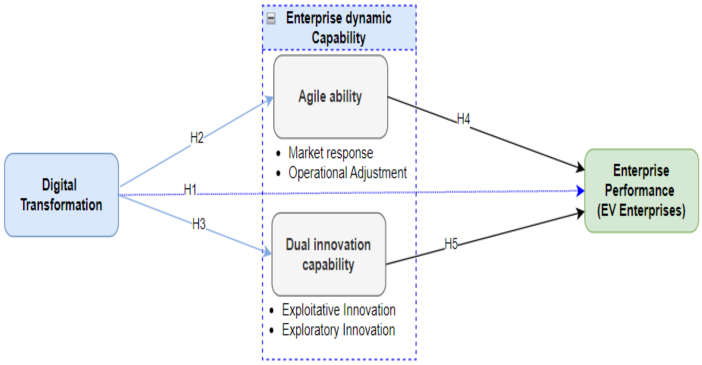

Figure 1. Theoretical framework.

3. Research methodology

The research design for this study used a quantitative approach to explore the complex relationships within the Electric Vehicles (EVs) Enterprises supply chain, focusing on digital supply chain transformation in the Guangxi Manufacturing Industry. The data was collected through a questionnaire survey using the five-point Likert scale. The scales were adapted from the existing literature. To have a broader demographic representation, the population of respondents included stakeholders involved in the Guangxi Electric Vehicle Manufacturing Industry who were selected using a stratified sampling technique. The data was collected through 200 respondents and the final analysis was run to the 197 responses. To choose the sample size we adopted the general rule of (Krejcie and Morgan, 1970), "where the population size is unknown or infinite, researchers may use a standard rule of thumb for determining an appropriate sample size. A commonly recommended guideline is that sample size shall be at least 30 times the number of utilized variables in the analysis". Though, as per this rule the total sample size required was 120 (4 × 30) responses but to keep the results more gregarious we collected the data from 200 respondents, and 3 responses were deleted because of invalid entries. A "snapshot" analysis was enabled by this method, showing the relationship between technology changes and business performance. The analysis of data entailed descriptive statistics that used SmartPLS to undertake structural equation modeling, reliability analysis with the use of Cronbach's alpha value; correlation and regression analyses; and adherence to ethical principles that protected integrity, dignity, and rights of all participants throughout the whole investigation process.

We use SmartPLS in our study due to its sophisticated features that can be used for complex models and small to medium samples such as in empirical research. Through SmartPLS, we can easily analyze the relationship between digital transformation, organizational agility, and innovation capabilities within the context of the manufacturing industry of Guangxi. It also can handle reflective and formative constructs, multicollinearity problems, and non-normal data distributions so that robust results are provided by this program. The usage of SmartPLS will enable us to conduct a thorough assessment of our measurement models and structural models that will determine how digitization impacts manufacturing performance in this specific region.

4. Results and analysis

This section provides an inclusive examination and analysis of data collected from different parts of the sector which shows how digital transformation influences and shapes EV enterprises' performance. The results capture the outcome of attempts to know if EV enterprises are taking on new technologies and if they are rationalizing their plans in line with agile and innovation capabilities. This section is about the interpretive ability of the findings derived from a diverse sample within the industry while adding to the wider debate concerning digitalization trends in the manufacturing industry.

4.1. Measurement model results

The output of the measurement model offers vital clues on dependability and validity in latent constructs within the study. The measurement model uses indicators such as indicator loadings, reliability coefficients (like Cronbach's alpha), composite reliability, and average variance extracted (AVE) to assess the degree of strength and consistency between observed and latent variables. These findings are basic for future analysis hence they help in understanding the structural model and testing some hypotheses. Below are a few important measurement results that we extracted through SmartPLS.

4.1.1. Outer loadings of the indicators

The loadings of the indicators reveal how strong relationship between individual observed (measured) variables and its corresponding latent construct. Higher loadings signify more association, hence authors have set a limit of ≥0.7 for this criterion (Nazeer et al., 2024; Shafiq and Soratana, 2020). This measurement model's figures have met the threshold requirements and the loading of indicators are represented in **Figure 2** and **Table 1** below.

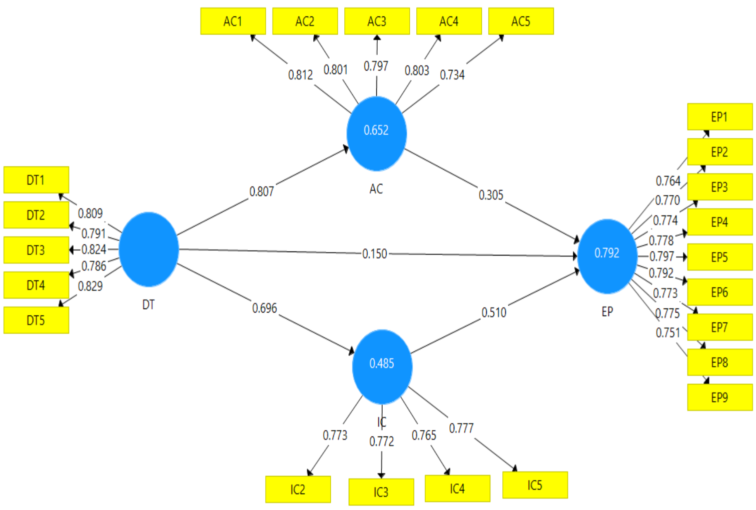

Figure 2. Measurement model.

Table 1. Quality criterion assessment.

List of variables	Measure	Outer loading	Values of cronbach's alpha	Composite reliability	AVE
Agile Capability	AC1	0.812	0.849	0.892	0.624
	AC2	0.801			
	AC3	0.797			
	AC4	0.803			
	AC5	0.734			
Digital Transformation	DT1	0.809	0.867	0.904	0.653
	DT2	0.791			
	DT3	0.824			
	DT4	0.786			
	DT5	0.829			
Enterprise Performance	EP1	0.764	0.917	0.931	0.601
	EP2	0.77			
	EP3	0.774			
	EP4	0.778			
	EP5	0.797			
	EP6	0.792			
	EP7	0.773			
	EP8	0.775			
	EP9	0.751			
Innovation Capability	IC2	0.773	0.774	0.855	0.596
	IC3	0.772			
	IC4	0.765			
	IC5	0.777			

4.1.2. Constructs reliability analysis

Mostly, internal consistency is tested by SmartPLS through the use of Cronbach's alpha. For example, Cronbach's alpha is a statistical measure that assesses how well items in a construct consistently tap into the same underlying phenomenon. High alpha values indicate high reliability, thus indicating that indicators within a construct have strong interconnections among themselves and effectively represent the intended latent variable. The minimum acceptable value for Cronbach's Alpha is "Cronbach's Alpha shall be ≥0.70".

Outer loadings in the table show the correlation between each indicator and its corresponding latent variable. Therefore, higher values have a stronger relationship with their constructs. The construct Agile Capability consists of five indicators AC1, AC2, AC3, AC4, and AC5 with outer loadings 0.812, 0.801, 0.797, 0803, and 0.734 respectively for example. These numbers show that the indicators in this construct are highly positively correlated with each other.

Cronbach's alpha ranges from 0.774 (Innovation Capability) to 0.917 (Enterprise Performance) as reported in **Table 1** which indicates a high level of internal consistency reliability for all constructs.

Another measure of internal consistency reliability is composite reliability which takes into account the different outer loadings of the indicator variables and is generally considered a more robust measure than Cronbach's alpha. However, this parameter has to be about 0.70 for it to be known as reliable enough; otherwise, it means less. **Table 1** shows that composite reliability ranges from 0.855 (Innovation Capability) to 0.931 (Enterprise Performance). All constructs have composite reliabilities above 0.7 which demonstrates good internal consistency reliability.

AVE (Average Variance Extracted): AVE helps test convergent validity by examining the proportion of its indicators' variances accounted for by a particular construct; this is indicated by higher AVEs above 0.5 which are indicative of satisfactory convergence. Table one reveals that the AVE values range between 0.596 for Innovation Capability and 0.653 for Digital Transformation. However, some constructs just breach or almost make this cut-off suggesting acceptable levels of convergent validity.

On the whole, Table's results indicate that some measures used in this study perform better than others since they exhibit acceptable levels of both reliability and validity-though these are not very high levels.

Table 2 gives Fornell-Larcker criterion results that are a guide for establishing discriminant validity in structural equation modeling (SEM). The Fornell-Larcker criterion compares the Average Variance Extracted (AVE) of each construct with all other constructs included in the model. For discriminant purposes, this correlation should be less than the average variance extracted for all constructs.

Table 2. Discriminant validity assessment (Fornell-Larcker criterion).

Variables	AC	DT	EP	IC
AC	0.79	-	-	-
DT	0.807	0.808	-	-
EP	0.814	0.751	0.775	-
IC	0.762	0.696	0.847	0.772

Bold typefaces on the diagonal show square roots of AVE values for all constructs while off-diagonal elements represent correlations between blocks (see **Table 2**). Agile Capability (AC) which has an AVE square root value of 0.790 is higher than AC's correlation with others such as Digital transformation and AC have a strong relationship having a correlative coefficient of 0.808; EP and AC have a strong positive correlation coefficient or 0.775 etc., hence Agile Capability exhibits discriminant validity of measurement items.

Furthermore, Agile Capability (AC), Digital Transformation (DT), Enterprise Performance (EP) and Innovation Capability (IC) square roots are above their correlations with other feature elements like AC, DT, EP, and IC.

The fulfilment of every design block by zero along with class squares along the diagonals and off-diagonal can be easily assessed by looking at **Table 2**.

Table 3 shows the Collinearity Statistics (VIF) that help to know the extent of correlation, **Table 3** offers the collinearity statistics, which are also called VIF. These values present the size of the correlation or linear association between numerous independent variables in a regression model. When there are strong correlations among the predictors, it is referred to as multicollinearity. It causes unstable and unreliable regression coefficients. One of these tests is called Variance Inflation Factor (VIF). It calculates VIF values for each variable. A VIF value equal to 1 means that there is no collinearity; whereas those above a certain threshold (usually five or ten) indicate multicollinearity. The larger the VIF becomes, the worse the multicollinearity situation.

Table 3. Outer values of VIF (collinearity statistics).

Measures	VIF
AC1	1.888
AC2	1.89
AC3	1.902
AC4	1.875
AC5	1.545
DT1	2.001
DT2	1.827
DT3	2.168
DT4	1.829
DT5	2.09
EP1	2.095
EP2	1.989
EP3	2.105
EP4	2.203
EP5	2.432
EP6	2.221
EP7	2.258
EP8	2.55
EP9	2.357
IC2	1.599
IC3	1.583
IC4	1.488
IC5	1.531

The joined table displays values from column Collinearity Statistics (VIF). Evaluating these numbers would enable researchers to determine whether their model suffers from multicollinearity issues. Lower values of VIFs than recommended levels like 5 or 10 mean the absence of a significant multicollinearity problem.

This part explores outer VIF Values (outer Variance Inflation Factor) that measure the degree of collinearities among indicators/measures within each construct/latent variable. High outer VIF Values with values greater than 5 or 10 for instance Collinearity Statistics (VIF) denote the presence of multicollinearity among indicators linked to a certain construct.

Table 3 shows outer population-wise VIF meeting the required threshold for each indicator in its construct. These figures can be used by researchers to observe issues related to cross-indicator variances that indicate problems in multi-colinearity.

4.2. Structural model results

In SmartPLS, the structural model examines how latent variables relate to each other and tracks these paths. This also helps to determine whether one variable has a direct or indirect impact on another. It also helps in assessing the goodness of fit of the model. **Figure 3** presents bootstrapping loadings that give standard errors and confidence intervals for path coefficients as well as provide robust statistical inference.

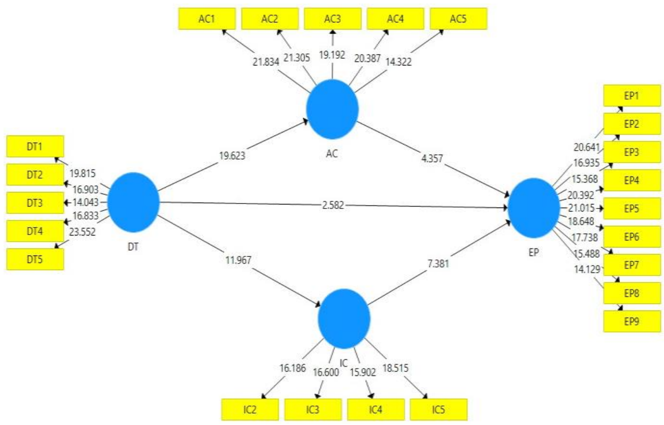

Figure 3. Structural model.

SmartPLS offers an analytical tool to measure and quantify how valid the constructs are, the strength of the hypothesized relationships, and the overall goodness-of-fit of a structural equation model.

The mean, standard deviation, *t*-value, and *p*-value of path coefficients between exogenous variables (AC → EP, DT → EP, IC → EP) and endogenous variables (DT → AC, DT → IC) are presented in **Table 4**.

Table 4. Mean, STDEV, *T*-Values, *P*-Values.

	Original Sample (O)	**Sample Mean (M)**	**Standard Deviation (STDEV)**	***T* Statistics (|O/STDEV|)**	***P* Values**
AC → EP	0.305	0.301	0.07	4.357	0
DT → AC	0.807	0.804	0.041	19.623	0
DT → EP	0.15	0.15	0.058	2.582	0.01
DT → IC	0.696	0.693	0.058	11.967	0
IC → EP	0.51	0.511	0.069	7.381	0

The following aspects can be observed from the table:

AC → EP has a significant positive effect with a *t*-value of 4.357 and a *p*-value of 0.000 which shows that there exists a direct proportionality.

DT → AC has a significant positive effect with a *t*-value of 19.623 and a *p*-value of 0.000 which shows that there exists a direct proportionality.

DT → EP has a significant positive effect with a *t*-value of 2.582 and a *p*-value of 0.000 which shows that the relationship is strong.

DT → IC EP has a significant positive effect with a *t*-value of 11.967 and a *p*-value of 0.000 this means that the relationship is strong, therefore, the IC → EP has a non-significant positive effect as its *t*-value is at 7.38 while its *p*-value was shown to be at 0.000 indicating weakness in their bonds together.

Table 5 shows that there are some important relationships between latent variables. On the one hand, there is a strong positive relationship between "AC" (Agile Capability) and "DT" (Digital Transformation), which is confirmed by the correlation coefficient of 0.807. Consequently, companies with high agile capability levels are also more likely to have higher levels of digital transformation in their operations. Moreover, it can be observed that "EP" (Enterprise Performance) shows a strong positive relationship with both "AC" (0.814) and "DT" (0.751), implying that corporations that exhibit greater agility and digital transformation tend to achieve better overall performance outcomes.

Table 5. Correlations analysis.

	AC	DT	EP	IC
AC	1	0.807	0.814	0.762
DT	0.807	1	0.751	0.696
EP	0.814	0.751	1	0.847
IC	0.762	0.696	0.847	1

Additionally, another positive correlation exists between "EP" (Enterprise Performance) and "IC" (Innovation Capability), which has a value of 0.847 as its coefficient. This means that enterprises with more robust innovation capabilities stand better chances of enhancing their performance. It should also be noted here that "IC" (Innovation Capability) has positive correlations with "AC" (0.762) and "DT" (0.696), although weaker than those associated with the aforementioned dependent variable.

The above findings indicate interrelationships among latent variables studied; agile capability, digital transformation, innovation capability, and enterprise performance being positively related to each other thus making them key elements for organizational success as well as competitiveness within Guangxi Electric Vehicle Manufacturing Industry's domain.

The coefficient of determination, also called *R*-squared, signifies the proportion of variance in the dependent variable which is predictable from the independent variables in a regression model. In this case, the *R*-squared values for latent variables such as "AC" (Agile Capability), "EP" (Enterprise Performance), and "IC" (Innovation Capability) give insights into how well the independent variables explain each respective dependent variable.

An *R*-squared value of 0.652 for "AC" (Agile Capability), indicates that about 65.2% of the variation in agile capability can be accounted for by some of the independent variables that are included in this model. The adjusted *R*-squared value slightly decreases to 0.650 after controlling for the predictors' number in this model.

Similarly, an *R*-Square value of 0.792 for "EP" (Enterprise Performance), means that around 79.2% of enterprise performance's variance can be understood based on the regression model's independent variables concerning it. However, upon adjusting for some predictors, the adjusted R-squared value reduces slightly to 0.789.

On the other hand, an *R*-squared figure is lower at 0.485 for 'IC' (Innovation

Capability), which means about 48.5% of innovation capability's variability has been explained by these factors among others put together under this model. The adjusted R-squared value remains lower at .482 after controlling for predictor numbers.

These results show that both agile capability and enterprise performance are highly dependent on independent variables used in building regression models as seen from their high r-square values as compared to innovation capabilities whose explanatory power is relatively lower implying the existence of other unobserved factors affecting innovation capabilities within Guangxi Electric Vehicle Manufacturing Industry context as shown above in **Table 6**.

Table 6. Results of *R* square and *R* square adjusted (Coefficient of Determination).

	***R* square**	***R* square adjusted**
AC	0.652	0.65
EP	0.792	0.789
IC	0.485	0.482

The hypothesis testing results in **Table 7** include mean, standard deviation, *T*-values, *P*-values, and decision for each hypothesis.

Table 7. Hypotheses results and decision.

Hypotheses		**Original Sample (O)**	**Sample Mean (M)**	**Standard deviation (STDEV)**	***T* Statistics (|O/STDEV|)**	***P* Values**	**Decision**
H1	AC → EP	0.305	0.301	0.07	4.357	0	Accepted
H2	DT → AC	0.807	0.804	0.041	19.623	0	Accepted
H3	DT → EP	0.15	0.15	0.058	2.582	0.01	Accepted
H4	DT → IC	0.696	0.693	0.058	11.967	0	Accepted
H5	IC → EP	0.51	0.511	0.069	7.381	0	Accepted

Hypothesis 1 (H1) examines the relationship between Agile Capability (AC) and Enterprise Performance (EP). The original sample has a mean value of 0.305 with a sample mean of 0.301 and a standard deviation of 0.070. This is confirmed by the T-statistic at 4.357 which shows that there is a significant relationship between AC and EP. Hence, the *P*-value is given as zero thus accepting this hypothesis. That means that digital transformation has a significant impact on manufacturing enterprise performance and digital transformation can help enterprises realize data-driven operation management processes. As well, decision-making efficiency is improved, production and operation costs decrease, operating profits increase, and ultimately there is improvement in enterprise performance.

Hypothesis 2 (H2) examines whether Digital Transformation (DT) affects Agile Capability (AC). The original sample has a mean value of 0.807 with a sample mean of 0.804 and a standard deviation of 0.041. This is confirmed by the T-statistic at 19.623 which shows that there exists significant relationships between DT and AC if any; Therefore P-value equals zero leading to acceptance of this hypothesis. That means that digital transformation has a significant positive impact on organizational agile capability, and digital transformation has a positive impact on the agility of market response, enabling enterprises to quickly capture changes in market demand by monitoring the external market, and then improve products and services to meet the individual needs of customers. At the same time, it has a positive impact on the agility of business adjustment, enabling enterprises to adjust internal business links according to changes in the market environment.

Hypothesis 3 (H3) investigates if DT impacts on EP. The original sample has a mean value of 0.150 with a sample mean of .150 and a standard deviation of 0.058. This implies that the T-statistic is at rest which means there is an important relationship between DT and EP because it stands at just about above average i.e., *P*-value=0.010 hence accepting these hypotheses. That means that digital transformation has a significant positive impact on organizational innovation capability and the digital technology and applied technology capabilities involved in the process of digital transformation can promote the establishment of dual capabilities of enterprises, enhancing the autonomy of employees, helping enterprises eliminate barriers to perception and access resources, promote knowledge transfer, explore new organizational processes, and enhance exploration capabilities.

Hypothesis 4 (H4) looks into how DT influences IC. The original sample has a mean value of 0.696 with a sample mean of 0.693 and a standard deviation of 0.058. This tells us that the t-statistic not taking off means there is an essential association amidst D.T plus I.C even though it falls slightly above average let alone more than half i.e., *P*-value=0.000 so accepting those hypotheses. That means that organizational agile capability has a significant positive impact on manufacturing enterprise performance. For manufacturing enterprises, achieving efficient production and maintaining the stability of the supply chain are keys to success. Agile capability can help manufacturing enterprises quickly perceive and respond to changing market demand, realize efficient production by reconstructing enterprise resources, and resist the risk of supply chain disruption. Market response agility under uncertain environmental conditions usually improves the competitive performance of enterprises by quickly capturing changes in market conditions, improving the speed of product customization, and shortening the reaction time.

Finally, Hypothesis 5 (H5) examines the relationship between IC and EP. The original sample has a mean value of 0.510 with a sample mean of 0.511 and a standard deviation of 0.069. Thus, the T-statistic at 7.381 indicates that there is a statistically important relation between IC and EP while *P*-value=0.000 hence accepting this hypothesis. That means that organizational innovation capability has a significant positive impact on manufacturing enterprise performance. This innovation ability accelerates the development of new products and enhances the market competitiveness of enterprise products. It greatly reduces the probability of successful model imitation, consolidates the dominant position of manufacturing enterprises, and improves the market competitiveness of manufacturing enterprises. In addition, when enterprises adopt proactive development strategies in the context of environmental fluctuations, the significant impact of dual capabilities on enterprise competitiveness and financial performance is particularly significant, and enterprises that can balance exploration and utilization activities tend to gain higher market competitiveness.

In general, all hypotheses are statistically significant, indicating that the variables examined in this study relate to each other as stated above.

5. Conclusion and recommendations

5.1. Conclusion

The outer loadings of measurement model analysis confirm strong relationships between indicators used to measure constructs such as Agile Capability, Digital Transformation, Enterprise Performance, and Innovation Capability and their respective latent variables. In addition, Cronbach alpha values higher than 0.7 for thresholds show that these constructs are reliable indicators since they are internally consistent. Moreover, composite reliability values above 0.7 for all constructs also support the reliability of the measurement model. Average Variance Extracted (AVE) values which show convergent validity indicate that most of them have acceptable levels implying they do effectively measure the intended latent variables.

The Fornell-Larcker criterion demonstrated discriminant validity between the constructs as their square roots exceeded correlations between them; thus each construct is separated from others. Collinearity statistics (VIF) indicated no serious multicollinearity in the model because VIF was less than is normally recommended. On the other hand, the structural model analysis showed significant positive links among Agile Capability—Enterprise Performance, Digital Transformation—Agile Capability, Digital Transformation—Enterprise Performance, Digital Transformation-Innovation Capability and Innovation capability—Enterprise performance. These relationships were supported by high t-values and low p-values denoting their statistical significance.

Additionally, Correlation analysis among latent variables revealed strong positive correlations between Agile Capability and Digital Transformation, Agile Capability and Enterprise performance, and Enterprise Performance and Innovation capability. This underlines why agile capability, digital transformation, and innovation capability contribute to enterprise performance within the Guangxi manufacturing industry.

Finally coefficient of determination (R-squared) indicates that a significant share of variance in agile capability or enterprise performance can be explained by independent variables in regression models while its value for innovation capability is relatively lower showing unobserved factors influencing innovation capabilities within this sector exist.

In conclusion, digital supply chain transformation, as found in the study result, has a positive influence on enterprise performance in the Guangxi manufacturing industry through enhancing agile capability, digital transformation, and innovation capability. These factors are interdependent and are critical drivers of the success of organizations operating within this industry.

5.2. Recommendations

Based on the above analysis, discussion, and conclusion following recommendations have been made for the professionals and EV manufacturers.

1) Improving agile capability and digitization.

The research reveals that there is a strong positive relationship between Agile Capability (AC) and Digital Transformation (DT), indicating that companies with high levels of agility are more likely to experience higher degrees of digital transformation in their operations. Hence, businesses ought to concentrate on increasing their agile capabilities thereby enabling them to implement successful digital transformation initiatives.

2) Investing in innovation capability.

While there exists a positive correlation between Innovation Capability (IC) and Enterprise Performance (EP) as indicated by this study, IC’s coefficient of determination is relatively lower compared with AC and EP. This suggests that innovation capabilities within the Guangxi Electric Vehicle Manufacturing Industry may be affected by some hidden determinants. Therefore, companies are advised to pay more attention to nurturing innovation to improve overall performance.

3) Strategic alignment for digital transformation initiatives.

Given the significant positive impact of Digital Transformation (DT) on both Agile Capability (AC) and Innovation Capability (IC), organizations should then align these transformational initiatives digitally with their agile as well as innovative strategies. This further helps in obtaining maximum benefits from digital transformation while maintaining consistency across varied organizational functions.

4) Continuous monitoring and improvement.

Like other key constructs such as Agile Capability, Digital Transformation, Enterprise Performance, and Innovation Capability which need continuous monitoring and improvement; this study highlights just how vital it is. Companies should regularly evaluate these using appropriate measurement tools or assessing frameworks, seeking areas for improvement over time.

5) Promoting collaboration and knowledge sharing.

Interrelationships among variables studied call for collaboration among departments involved in supply chain management together with digital transformation programs aimed at fostering creativity enhancement, and adaptability to change among employees influencing overall performance within an organization.

6) Investment in employee training and development.

To leverage DT initiatives successfully while improving organizational capabilities; firms must invest in employee training and development programs. These programs equip employees with skills necessary for adaptation to technological changes, innovation-driving forces, and contribution to organizational success.

In short, agile capability, digital transformation, innovation capability, and how these affect enterprise performance in the context of Guangxi Electric Vehicle Manufacturing Industry were examined in this research. Consequently, by implementing these recommendations companies will be better positioned to enhance their performance thus maintaining competitiveness in the increasingly digital and dynamic nature of the business environment.

5.3. Managerial implication

Agile capabilities are at the center of digital transformation, implying that EV manufacturing businesses should focus on adaptive planning and continuous improvement to enhance their digital initiatives, thus creating a need for investment in innovation capabilities. Investing in innovative capabilities is also stressed, requiring the promotion of artistic culture and technological growth to sustain a competitive edge. Maximizing benefits and ensuring organizational coherence thus require aligning digital transformation initiatives with agile and innovative strategies. There are some key constructs such as agile capability, digital transformation, and innovation capability which need to be continuously monitored for evaluation purposes. Promoting collaboration and knowledge sharing within the EV manufacturing organization is important because it enhances creativity and adaptability which in turn affects overall performance. Furthermore, organizations need to make significant investments in employee training and development to equip them with skills necessary for both technology adaptation and innovation which eventually results in organizational success. Consequently, companies within the Guangxi EV manufacturing industry can adopt these recommendations to improve performance and hence remain competitive in a highly digitalized dynamic business environment.

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