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PRODUCTION EFFICIENCY: ROLE OF DECISION MAKING FACTORS, BIG DATA AND PREDICTIVE ANALYTICS

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Abstract: *This research explores the impact of automated decision-making and decision-making competence on production efficiency in the manufacturing industry of Saudi Arabia. Additionally, it examines the moderating role of big data and predictive analytics, and problem-solving decision-making on the relationship of automated decision-making and decision-making competence. A quantitative approach was employed, collecting data from 283 productions, line, and shift managers, as well as engineers working in manufacturing industry. A structured questionnaire was used, adopting scales from previous research to measure the core constructs. The data were analyzed using Stata-SEM, with confirmatory factor analysis (CFA) to validate the measurement model and path analysis to test the hypothesized relationships. Findings: The results show that attitudes towards automated decision-making and decision-making competence significantly influence production efficiency. Decision-making competence also mediates the relationship between attitudes towards automated decision-making and production efficiency. Furthermore, big data and predictive analytics, as well as problem-solving decision-making, were found to significantly moderate the relationship of automated decision-making and decision-making competence; enhancing production outcomes. This study contributes to the literature by providing empirical evidence on the role of decision-making competence and the integration of advanced data analytics in boosting production efficiency. It offers practical implications for managers in the manufacturing industry, emphasizing the importance of leveraging technology and enhancing decision-making capabilities to optimize production processes.*

Keywords: *Automation, Decision making competence, Big data and predictive analytics, Production efficiency.*

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1. Introduction

The integration of automated decision making's (ADM) systems into contemporary production processes had a huge shift in how organizations align optimization and efficiency. With increased reliance on advanced technologies such as artificial intelligence, big data, and predictive analytics in all industries, ADM systems became critical tools for improving the efficiency of production while streamlining decision-making processes (Ma & Chang, 2024). ADM decides autonomously and, by and large, does not engage with the human brain via algorithms and machine learning techniques that tend to reduce dependence on humans for most routine or data-driven scenarios (Ara et al., 2024). Such systems have been very transformative in areas like manufacturing, supply chain management, and logistics, where fast and accurate decisions can make all the difference in operational outcomes (Chen, 2024). Though ADM offers a lot, effectiveness for production efficiency enhancement depends upon a factor set comprised of decision-makers' attitudes, the quality of their decision-making competency, and technological infrastructure underpinning the systems (Ivanov & Webster, 2024).

Subsequently, certain empirical studies provided a crucial foundation for comprehending the associations between ADM and production outcomes (Nudurupati et al., 2024). For instance, studies indicate that a favorable attitude towards ADM can greatly encourage its adoption and successful application for the improvement of productivity and little reduction of operating expenses (Srioguz & Miser, 2024). Such combinations of ADM, big data, and predictive analytics proved to further optimize production processes, making it possible to get insight into real-time information within systems and expect future challenges or opportunities (Watts et al., 2024). Other research by Bickley et al. (2024) held that decision-making competence is instrumental in defining the manner in which effective ADM systems are used in a production environment. Such competence enables the manager to make more informed, strategic decisions when working with automated systems, thereby maximizing their potential efficiency-improving benefits (Samokhvalov, 2024). While these findings are very interesting, they indicate that there is still some need to further research the potential combined effects of these variables and their interaction influences on the outcomes of production processes (Castor et al., 2024; Samokhvalov, 2024).

While the amount of research on ADM has been increasing, still, quite a lot of gaps exist in the literature (Castor et al., 2024), notably in the relationships existing between attitudes and decision-making competence with other external moderating factors (Virmani et al., 2024) for example, big data and problem-solving capabilities (Watts et al., 2024). Most studies have hence concentrated narrowly on the direct effect of ADM on production efficiency without providing an explanation of how individual and organizational factors, such as decision-making competence, mediate or moderate that relationship (Nuryanto et al., 2024). In addition, despite the fact that the role of big data in ADM systems is being increasingly recognized to improve such systems, there is hardly any empirical study that attempted to test its moderating effects on the relationship between the adoption of ADM and production efficiency (Brau et al., 2024). In the same way, an in-depth study on the impact of problem-solving decision-making as a moderating variable was never carried out, considering that this might ultimately influence in what ways attitudes toward ADM can be translated into success operations (Galeazzo et al., 2024). These gaps suggest that further research in the combination of variables should be undertaken to analyze how they play both moderating and mediating roles in a relationship with ADM-production efficiency (Kumar et al., 2024).

The research is theoretically based in both the decision-making theories and the Technology Acceptance Model (TAM), supporting the relationships to be examined. TAM provides insight into the determinants of technology adoption Chen et al. (2024), based on the critical factors of perceived usefulness and ease of use, suggesting that attitudes toward ADM will play a key role in its successful implementation. In addition, decision-making competence theory illustrates that cognitive skills play an important role in determining the effectiveness of decisions in complex and data-driven environments (Aseeri & Kang, 2023). Another set of theories used in this research are with respect to big data and predictive analytics, which state that these technologies will help revolutionize decision-making with better quality and timeliness of information (Castor et al., 2024). By putting together the different theoretical approaches, this study attempts to fill the gaps in literature and explore what relationships exist between attitudes toward ADM, decision-making competencies, and production efficiency, all in consideration of moderating roles of big data and problem-solving decision making. The main objectives of the present study are to examine how such factors interact with and impact production efficiency, and provide actionable insights for organizations seeking to enhance their ADM systems (Arias-Gonzáles et al., 2023).

2. Literature Review

Automated decision making is one of the most impactful forms in industrial production processes. They have been heavily integrated into manufacturing environments to optimize operations with limited human intervention in the process of routine decision-making (Liu et al., 2023). Such systems utilize algorithms based on machine learning and online data analysis to analyze variables relevant in production, forecast outcomes, and change operations based on these analyses (Kar & Kushwaha, 2023). Such automation allows for the potential fast response to fluctuating production conditions like supply chain interruption or machinery failure; it would decrease the time spent in idle conditions and thereby optimize the usage of resources (Caputo et al., 2023). Studies have found that ADM are positively related to higher measurements of production rates that were reported by firms to achieve greater levels of output, shorter lead times, and greater use of productive assets (Gangwar et al., 2023). For instance, dynamic adaptation by the production line regarding historical performance data and actual production plans combined with the availability of resources results in optimization of continuity without bottlenecks (Bousdekis et al., 2023). Encouraging significant advancement in predictive maintenance as well as quality control integration is the fact about the incorporation of ADM systems into production workflows (Di Vaio et al., 2022). Through constant equipment and production quality monitoring metrics, ADM can predict equipment failures or quality deviations, thus creating a 'window of opportunity' for the occurrence of preemptive maintenance or corrective action without disrupting operations (Yu et al., 2022). Overall, this proactive form of problem-solving maximizes production output due to less unexpected downtime and defective products costs. Another positive result of ADM is a more agile production environment that is responsive and flexible (Rosin et al., 2022). Adjustments to the schedules of production, labor allocation, or material inputs automatically occur on the fly based on real-time data. The resulting agility in responsiveness to changes in internal and external factors enables manufacturers to hit customer demands with greater precision and go beyond merely the reduction of waste to achieve even more sustainable production practices (Sharma & Villányi, 2022). Furthermore, ADM research also indicates that the decision-making of management eventually builds up in the long term due to providing good information along with predictive abilities to companies for the improvement of strategic planning (Rožanec et al., 2022).

Attitudes toward ADMs are an important determinant of its successful adoption and its impact on production efficiency (Rodríguez-Espíndola et al., 2022). Attitude refers to the cognitive, affective, and behavioral predispositions of individuals or organizations toward ADM systems (Bagshaw, 2017). Considered under these attitudes are trust perceptions of reliability, ease of use, and perceived benefits versus the risks associated with the automation of decisions in production environments (Kaun et al., 2024). Production efficiency refers to the degree at which the production processes can transform inputs, such as labor, materials, and time, into output with little waste and maximum quality (Nilashi et al., 2023). If employees or decision makers carry a positive attitude toward ADM, then they are in a good position to embrace and incorporate these systems into their operations effectively, making them streamline operations, minimize errors, and realize optimal use of resources (Ma & Chang, 2024). However, the effectiveness of ADMs would be reliant on attitude towards itself that exists as a number of negative attitudes such as a fear of job displacement, the loss of control or lack of reliability in automated systems may thus limits full utilization and potential efficiency gains (Chen, 2024; Pathmanathan et al., 2022).

Prior empirical research has focused on the relationship between technology adoption and organizational efficiency, providing insights into the role of attitude in influencing the success of technology (Nudurupati et al., 2024). For example, studies based on the TAM model have identified that perceived usefulness and perceived ease of use are core variables that determine adoption behavior towards technology because positive perception leads to higher levels of acceptance and utilization (Watts et al., 2024). Studies in the realm of ADM have shown that if the workers and managers find ADM systems beneficial and reliable, such systems tend to convey significant improvements in production outcomes (Samokhvalov, 2024). To illustrate, an empirical study by Virmani et al. (2024) revealed that the beneficial attitude toward automated systems led to better operational efficiency in manufacturing settings while companies reported better output and fewer errors. Similarly, Brau et al. (2024) observed that more agile and responsive in production were firms that entirely implemented ADM, especially when the supply chain breaks up or changes direction in the supply channel. Organizations that were hostile or had much antagonism towards automation usually had inefficiencies since the system was compromised by several human interventions and delays that it could not work near its potential to optimize processes (Kumar et al., 2024).

On empirical basis, the hypothesis is well supported in the sense that attitudes toward ADM do have a significant impact on efficiency in production (Aseeri & Kang, 2023). Being positive toward ADM will create an atmosphere for full exploitation of the technology and would then more easily result in measurable improvement in efficiency through integration in the processes of production (Liu et al., 2023). Negative attitudes thus become barriers to adoption of ADM and subsequently reduce effectiveness. The literature clearly reveals that using technical capabilities of automatic systems and relying solely upon them cannot guarantee success; rather, such usage depends on a blend of psychological and organizational factors (Caputo et al., 2023). For example, among organizations that spend money on training and cultivate a positive culture toward the adoption of ADM, greater efficiency is likely to be achieved over peers because employees trust the system and can work it proficiently (Gregório et al., 2020). The development of this hypothesis would suggest that attitudes about automation are critical determinants in the impact ADM has on production efficiency (Kaun et al., 2024). It opens possibilities for significant operational improvements through efforts to improve attitudes toward automation.

H1: *Attitudes towards automated decision making significantly influences the production efficiency.*

Empirical research on decision-making competence constantly has indicated that this dimension takes a major role in influencing many organizational outcomes, but particularly with respect to operational and production efficiency (Donelan et al., 2016). It can be broadly defined as the effectiveness or capability of an individual or organization to make decisions depending on the information available, most often situated in knotty and high-stake situations (Ara et al., 2024). Studies have shown that decision-making competence, with skills in problem-solving, risk assessment, and the ability to weigh options, is an influence on the efficiency of production processes (Ivanov & Webster, 2024). For instance, how Srioguz and Miser (2024) posit that high decision-making competence augments the accuracy and timeliness of decisions, which definitely reduce inefficiency in operations and increase productivity. Bickley et al. (2024) also discovered that competent decision-makers better are able to foresee in advance interruptions to production and consequently ensure that there are adequate resources in place to minimize these negative disturbances. Also, they come up with a flexible response toward unanticipated disturbances; hence, all these results in overall better production efficiency (Castor et al., 2024). These studies point out the connection between decision-making competence and optimized production outcomes, then through the processes and influences of effective decision-making to facilitate a smooth operation or workflow (Nuryanto et al., 2024).

These empirical grounds lead to theoretical support and practical evidence for the hypothesis concerning decision-making competence as being a significant influencer of production efficiency (Galeazzo et al., 2024). With strong competence in decision-making, decision-makers have a better edge to understand the complexity of the production environment, spot inefficiencies in the production process, and implement solutions that streamline workflows (Chen et al., 2024). For example, studies have shown that effective decision-makers are likely to be more experienced in utilizing data analytics and other sources of support in decision-making to improve the production planning and scheduling processes in realizing decreased lead times and low wastes (Roehl, 2023). It facilitates the synthesis of information that can be applied in real-time production contexts, thus more effectively using resources and labor to enhance the overall productivity of the organization (Kar & Kushwaha, 2023). Besides, in highly automated or technologically advanced production settings, decision-making competence is much more critical because the integration of sophisticated systems requires decision-makers to navigate intricate interdependencies and strategic choices about technology deployment and optimization (Gangwar et al., 2023). These studies affirm the existence of a direct link between competent decision-making and efficient production outcomes. For instance, Di Vaio et al. (2022) state that firms operating under the helm of decision-makers characterized by a high level of decision-making competence have increased chances of adopting continuous improvement practices like Lean Manufacturing or Six Sigma, which, above all, are aligned with waste elimination and improvement in efficiency over time (Rosin et al., 2022). Efficiency gain from informed decision-making-driven continuous improvements contributes to an environment of better adaptability and resilience in production, as efficiency gains are kept intact and compounded (Rožanec et al., 2022). This therefore means, the greater the competence of the decision-maker, the better the uncertainties in the production process, such as changes in demand and supply chains, can be managed through efficient speedy adjustments that work to keep production going without losing efficiency (Bagshaw, 2017). It is also within this framework that keeping short-term concerns about operational needs aligned with long-term strategic consideration will once again weigh heavily on decision-making competence as an influential determinant of productivity as a supporting hypothesis in the direction that greater decision-making results in more productive results in production (Kaun et al., 2024; Mubarak, 2023).

H2: *Decision making competence significantly influences the production efficiency.*

Empirical work has extensively investigated the mediating role of decision-making competence in various organizational and operational relationships, especially in technologically driven contexts (Ma & Chang, 2024). The research studies conducted have shown not only that decision-making competence directly impacts production efficiency but also that it was a very crucial intermediary relationship through which other factors, like attitudes toward technological systems, impacted subsequent outcomes on operations (Ivanov & Webster, 2024). For instance, Watts et al. (2024) found that attitudes toward new technologies are more likely to be implemented by competent decisors so that more could get out of organizational performance. Attitudes toward automated systems, in technologically advanced production areas, are mainly accepted or rejected by the individuals, depending on the acceptability of the system and the decision-making competence of the key personnel (Castor et al., 2024). Decision-making competence allows individuals to make better decisions regarding how automation technologies should be implemented and managed, which leads to better operational outcomes like production efficiency (Brau et al., 2024). Clearly, attitudes toward automation are important but when filtered through the lens of decision-making competence, they have a significantly greater impact.

Such empirical underpinnings lead to substantial support of hypothesis building on the relationship between attitudes toward ADM and production efficiency through a mediator: decision-making competence (Chen et al., 2024; Liu et al., 2023). Positive or negative attitudes toward ADM are hereby conceived in operational terms on instrumental strategies through which they may influence production outcomes (Liu et al., 2023). For example, those people who are favorable toward ADM yet not really skillful at decision-making will struggle to fully capitalize on all that ADM can offer to their productivity (Gangwar et al., 2023). Conversely, individuals with favorable attitudes to ADM and also high decision-making ability will be in a position to integrate ADM with the flows of production in a way that maximizes all potentials which yield efficiency gains (Yu et al., 2022). This mediating effect is important because it draws attention to the fact that attitudes by themselves are not good enough as a basis to bring about efficiency in production; it is decision competence that bridges the gap between attitude and action (Rožanec et al., 2022). If decision competence is high, managers would apply their favorable attitudes toward ADM toward the actualization of more efficient scheduling of inputs, optimal allocation of resources, and process optimization-all of which are immediate antecedents of greater efficiency (Gregório et al., 2020; Yang et al., 2023).

The hypothesis also falls in line with the broad corpus of research attempting to understand the relationship between technology adoption and human attitudes towards the resultant decision making processes (Nilashi et al., 2023). Many studies have demonstrated that competencies of decision-making most significantly determine the terms through which an organization adopts and implements new technologies, for they very often serve as the significant mediator that illustrates how successfully technology can be integrated into its use within the organization (Ara et al., 2024). This mediation is even more important in the context of ADM because of the complexity and scale of automation in modern processes of production (Nudurupati et al., 2024). Thus, competent decision makers are able to deal with the challenges expected by ADM systems, namely the continuous monitoring and adjustment, while making informed, timely decisions in alignment with positive attitudes toward automation (Bickley et al., 2024). This has the ability to mediate attitudes and production efficiency and highlights a position taken by this essay concerning the central role that decision-making competence must play in ensuring that the potential benefits of ADM are fully realized (Virmani et al., 2024). Therefore, the hypothesis that decision-making competence significantly mediates the relationship between attitudes toward ADM and production efficiency is highly supported, suggesting that organizations aiming to improve efficiency should not only foster positive attitudes toward automation but also enhance the decision-making competence of personnel to fully benefit from such technologies.

H3: *Decision making competence significantly mediates the relationship of attitudes towards automated decision making and the production efficiency.*

The role of Big Data and Predictive Analytics (BDPA) in modern industries is slowly taking over in shaping people's choice in decision making (Galeazzo et al., 2024). Studies have emphasized that improvement in data-driven decision making has been observed because of the introduction of BDPA by providing more insight (Aseeri & Kang, 2023), tighter forecasting (Bousdekis et al., 2023), and less uncertainty in operational environments (Rosin et al., 2022), thus this capability can be very instrumental for manufacturing industries (Rodríguez-Espíndola et al., 2022). Optimal efficiency of production and resource allocation are key issues in such industries (Kaun et al., 2024). Attitudes toward automated decision making will determine whether the systems are fully accepted and implemented (Chen, 2024). Integrated with BDPA, decision makers can rely on large amounts of data to create better and more accurate choices, thereby improving decision-making ability (Srioguz & Miser, 2024). At present, research has established that BDPA not only enables analysis of real-time data but also provides a much more organized and secure setting for a decision maker to work (Abdurrazaq & Fahad, 2023; Samokhvalov, 2024). It is therefore hypothesized that BDPA significantly moderates the relationship between attitudes toward automated decision-making and decision-making competence by enhancing the quality and confidence in the decision-making processes.

H4: *Big data and predictive analytics significantly moderate the relationship of attitudes towards automated decision making and the decision-making competence.*

Problem-solving decision-making becomes a significant part of any managerial job, but especially when the production environment is even more intricate, as in manufacturing (Nuryanto et al., 2024). Researches show that the strategy for problem-solving can enable managers better to solve the operational problems, improve process flows, and also enhance the outcomes of productions as aforementioned by (Sharma & Villányi, 2022). Attitudes toward automated decision making shape the use of technology within such settings, according to (Ara et al., 2024). When decision-makers are positive toward automation, then they will likely utilize automated tools more productively in their processes of problem-solving, thereby enhancing overall decision-making competence (Samokhvalov, 2024). Moreover, the decision-making process that requires problem-solving skills is usually undertaken with flexibility and adaptability, which become essential when working with automated systems (Roehl, 2023). Consequently, problem-solving decision-making can neutralize the attitude towards automation influence on the competency of decision-making by offering a more fluid and responsive technique of addressing production problems (Galeazzo et al., 2024). For this hypothesis, it would be that problem-solving decision-making forms a stronger bond with the attitude toward automated decision-making, making it a great influencer of managerial competencies (Srioguz & Miser, 2024).

H5: *Problem solving decision making significantly moderates the relationship of attitudes towards automated decision making and the decision-making competence.*

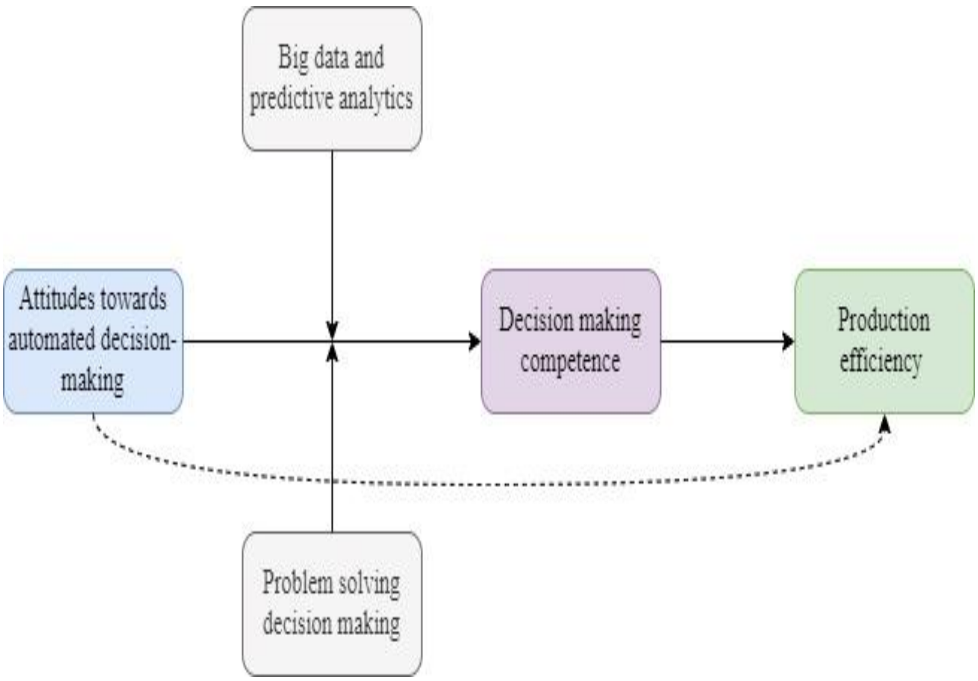

Figure 1: Theoretical Model

3. Methodology

This study focuses on the Kingdom of Saudi Arabia's manufacturing industry specifically to investigate how automated decision-making, competent decision-making, and the moderating function of big data analytics and problem-solving decision-making impacts production efficiency. The method of this study is quantitative in nature and adopted a cross-sectional survey to collect and analyze data from managers and engineers, who were directly involved in the production processes. The sample included 283 respondents, which comprise production managers, line managers, shift managers, and engineers working in different factories under the manufacturing sector. It was through this stratified random sampling technique that the respondents were selected to enable inclusion of people with a wide range of experiences and decision-making responsibility. A structured questionnaire was designed for collecting data, and the survey instrument was developed on established scales adopted from previous research works. Validated scales taken from previous studies were adopted for measuring all constructs of attitudes toward automated decision-making, big data and predictive analytics, problem-solving decision-making, and production efficiency.

Table 1: The Reference studies of questionnaire

Sr. No	Constructs of the research	Based on	Resource
1	Attitudes towards automated decision making	9 items	(Kaun et al., 2024)
2	Decision making competence	14 items	(Donelan et al., 2016)
3	Big data and predictive analytics	3 items	(Nilashi et al., 2023)
4	Problem solving decision making	6 items	(Gregório et al., 2020)
5	Production efficiency	3 items	(Bagshaw, 2017)

The collected data was then analyzed by means of Stata-SEM that allowed the estimation of multiple inter-relations between these variables simultaneously, thus supporting testing of the advanced hypotheses. The reason for this choice was because it permits greater modeling of complex inter-relations involving latent variables and includes mediating and moderating effects, hence critical for this study's objectives. Employing confirmatory factor analysis, the measurement model was validated and shown to be reliable. Path analysis was then adopted to test the hypothesized direct, mediating, and moderating relationships. Overall, the methodological approach was adopted as it suits best to provide rich empirical evidence regarding the relationships between attitudes toward automated decision-making, decision-making competence, and production efficiency, all of which will be considered in line with a primary check with the moderating influence of big data analytics and problem-solving decision-making.

4. Results

The CFA in Table 2 shows the measurement of latent variables using standardized coefficients and statistical significance for testing the measurement model. All the items, including ATAD2 (0.541, z = 10.465, $p < 0.001$), ATAD3 (0.567, z = 10.144, $p < 0.001$), among others all load significantly on the latent construct with strong factor loading. Finally, the "Decision-Making Competence" variable also had significant loadings for items such as DMC2 (0.589, $z = 11.070$, $p < 0.001$) and DMC3 (0.556, $z = 66.774$, $p < 0.001$). The constraint items, whose coefficients were set at 1.000 for identification, could be used as reference points to scale the factors.

In other words, the loadings of all the items under the constructs "Big Data and Predictive Analytics", "Problem Solving Decision Making", and "Production Efficiency" all have a high statistical significance $p < 0.001$, thereby strengthening the validity of the measurement model. These findings thus validate that the items appropriately measure their respective constructs, hence ensuring that the resultant model is reliable for further structural analysis.

Table 2: Confirmatory Factor Analysis

Measurement	OIM Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
ATAD1	1.000	(constrained)				
ATAD2	0.541	0.042	10.465	0.000	0.371	0.530
ATAD3	0.567	0.045	10.144	0.000	0.145	0.552
ATAD4	0.163	0.081	8.531	0.000	0.248	0.808
ATAD5	0.208	0.038	71.605	0.000	0.245	0.755
ATAD6	0.215	0.064	2.953	0.000	0.413	0.693
ATAD7	0.593	0.048	9.079	0.000	0.498	0.688
ATAD8	0.648	0.051	9.594	0.000	0.548	0.741
ATAD9	0.561	0.078	8.066	0.000	0.149	0.723
DMC1	1.000	(constrained)				
DMC2	0.589	0.056	11.070	0.000	0.553	0.706
DMC3	0.556	0.040	66.774	0.000	0.198	0.699
DMC4	0.481	0.056	8.010	0.004	0.401	0.654
DMC5	0.000	0.000	0.000	0.000	0.000	0.000
DMC6	0.648	0.054	8.799	0.000	0.547	0.608
DMC7	0.505	0.072	10.056	0.000	0.272	0.873
DMC8	0.536	0.083	7.937	0.000	0.210	0.759
DMC9	0.606	0.043	59.125	0.000	0.075	0.178
DMC10	0.082	0.085	9.024	0.000	0.339	0.884
DMC11	0.649	0.051	9.465	0.000	0.549	0.595
DMC12	0.681	0.064	9.612	0.002	0.561	0.685
DMC13	0.143	0.080	8.652	0.000	0.245	0.810
DMC14	0.645	0.037	69.342	0.000	0.110	0.337
BDPA1	1.000	(constrained)				
BDPA2	0.643	0.035	74.558	0.000	0.101	0.368
BDPA3	0.554	0.048	8.688	0.000	0.460	0.641
PSDM1	1.000	(constrained)				
PSDM2	0.685	0.050	10.055	0.000	0.593	0.638
PSDM3	0.710	0.036	75.631	0.000	0.177	0.406
PSDM4	0.435	0.049	6.943	0.000	0.343	0.531
PSDM5	0.692	0.054	9.918	0.000	0.592	0.644
PSDM6	0.278	0.036	75.666	0.000	0.305	0.445
PE1	1.000	(constrained)				
PE2	0.488	0.037	73.009	0.000	0.302	0.694
PE3	0.672	0.053	9.640	0.000	0.575	0.626

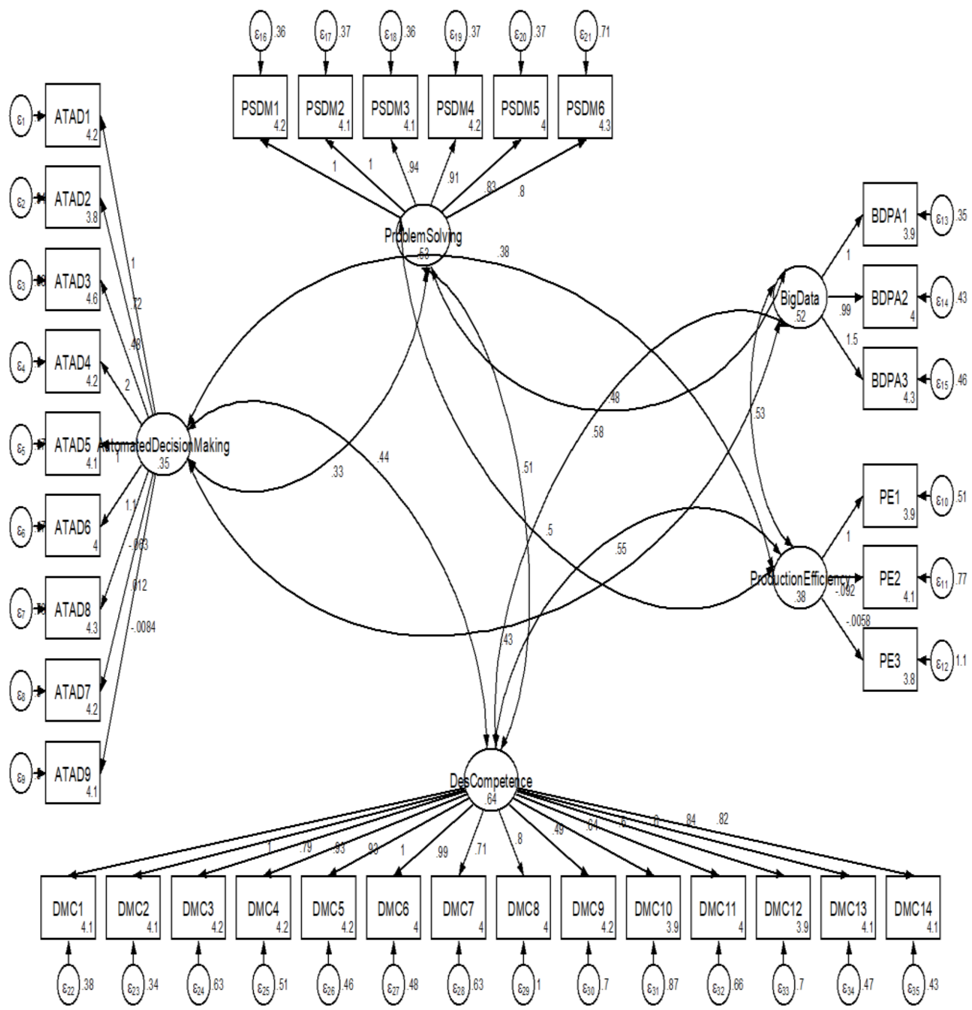

Figure 2: Estimated Model

Table 3 demonstrates the reliability and construct validity statistics of latent constructs in terms of Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). It states that all variables attain acceptable internal consistency reliability. For instance, Cronbach's Alpha of "Attitudes toward Automated Decision Making" is 0.726, CR 0.909, and AVE 0.502-all indicating good construct reliability and proper convergent validity, considering that AVE is greater than 0.50. Similarly, "Decision Making Competence" has Cronbach's Alpha of 0.780, CR of 0.856 and AVE of 0.505 that have sound measurement. This second scale refers to "Big Data and Predictive Analytics," which has a high reliability: Cronbach's Alpha = 0.822, CR = 0.889, and AVE = 0.533, as seen in Table 3, allowing for the validity of this variable. Other constructs including "Problem Solving Decision Making" (Cronbach's Alpha = 0.845, AVE = 0.517) and "Production Efficiency" (Cronbach's Alpha = 0.764, AVE = 0.645) also indicate measurement of validity and reliability that suggests the model is ready for further structural testing.

Table 3: Measurement Items Fitness Statistics and Variables reliability and validity

Variable	Indicator	Original Sample	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Attitudes towards automated decision making	ATAD1	0.643	0.726	0.909	0.502
	ATAD2	0.692			
	ATAD3	0.713			
	ATAD4	0.646			
	ATAD5	0.552			
	ATAD6	0.545			
	ATAD7	0.584			
	ATAD8	0.595			
	ATAD9	0.769			
Decision making competence	DMC1	0.564	0.780	0.856	0.505
	DMC2	0.515			
	DMC3	0.614			
	DMC4	0.660			
	DMC5	0.695			
	DMC6	0.588			
	DMC7	0.612			
	DMC8	0.625			
	DMC9	0.769			
	DMC10	0.807			
	DMC11	0.648			
	DMC12	0.683			
	DMC13	0.574			
	DMC14	0.502			
Big data and predictive analytics	BDPA1	0.736	0.822	0.889	0.533
	BDPA2	0.644			
	BDPA3	0.671			
Problem solving decision making	PSDM1	0.685	0.845	0.841	0.517
	PSDM2	0.542			
	PSDM3	0.535			
	PSDM4	0.664			
	PSDM5	0.654			
	PSDM6	0.752			
Production efficiency	PE1	0.711	0.764	0.808	0.645
	PE2	0.738			
	PE3	0.698			

Table 4 are chi-square fit statistics that indicate relative goodness of fit of the model against saturated model. The likelihood ratio test statistic for the model versus the saturated model is 7140.722, with a p-value of 0.000, which means that it is highly significantly different between the hypothesized model and a perfectly fitting model. For that reason, the chi-square baseline model statistic, chi2_bs, at 3225.039 with a p-value of 0.000 also points out a comparison between the baseline and saturated models. Even though these fit statistics are statistically significant due to the sample size of the research, they imply that other model fit indices must be paid more attention so that the adequacy of the model might be better appreciated.

Table 4: Chi-square Fit statistics

Fit statistic	Value	Description
Likelihood ratio	7140.722	model vs. saturated
p > chi2	0.000	
chi2_bs(2728)	3225.039	baseline vs. saturated
p > chi2	0.000	

Table 5 shows R-square statistics for the endogenous variables. These provide the explanation regarding the explanatory value of the constructs. "Attitudes towards Automated Decision Making" explains 24.2% of the variance in production efficiency, and "Decision Making Competence" has stronger explanatory power, accounting for 41% of variance. The strongest predictive power is exhibited by "Big Data and Predictive Analytics"; overall, it explains 50.7% of the variance, thereby showing that it would be highly influenceable over changes in production efficiency. "Problem Solving Decision Making" explained 31.3% of the variance. The SRMR of the saturated model stands at 0.060 while that of the estimated model is 0.064; within acceptable limits, thus generally suggesting that the model has good fit.

Table 5: R-square statistics Model Goodness of Fit Statistics

	Saturated Model	Estimated Model	R Square
SRMR	0.060	0.064	
Attitudes towards automated decision making			0.242
Decision making competence			0.410
Big data and predictive analytics			0.507
Problem solving decision making			0.313

The path analysis results summarized in Table 6 offer major insights into the relationship between different constructs under study. Attitudes toward automated decision-making show positive influence on production efficiency, with a coefficient of 0.620, as supported by z = 9.474 and p < 0.000; in other words, the favorable attitudes toward automation work directly to enhance production efficiency. As can be seen in Table 6, decision-making competence is as important as a predictor of production efficiency, with a coefficient of 0.679 (z = 10.888, p < 0.000), and it indicates that persons who are more competent in decision making would give in to better performances in terms of the production outcome.

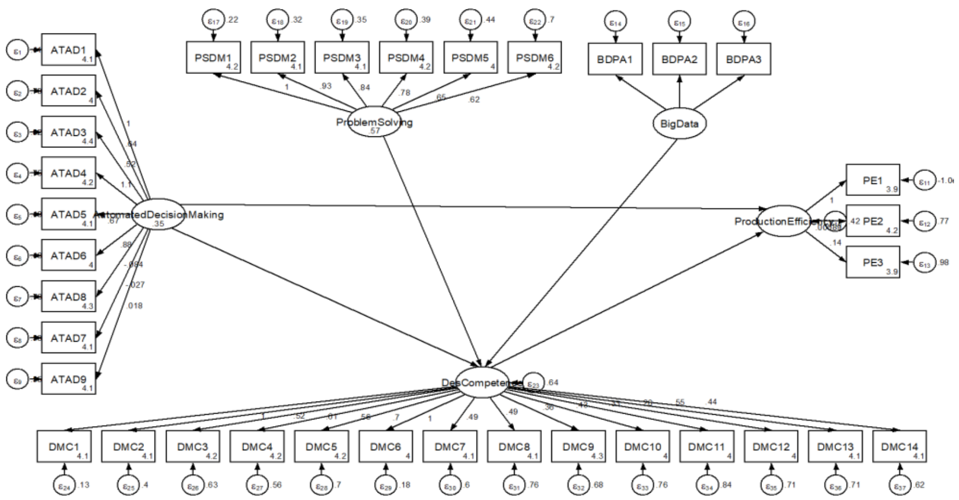

Figure 3: Structural Model for Path Analysis

Decision-making competence also highly mediates the relationship between attitudes toward automated decision making and production efficiency. This is indicated by a coefficient of 0.668 ($z = 9.736$, $p < 0.000$). The mediation effect is indicative of the fact that decision-making competence is significantly essential for the conversion of positive attitudes toward automation into improved production efficiency. The moderation effects of BDPA and problem-solving decision-making are also significant. BDPA significantly moderates the attitude toward automated decision-making and decision-making competence with a coefficient of 0.661 ($z = 9.790$, $p < 0.000$), thereby making the process of decision-making better and more effective. Finally, problem solving in decision making moderates this relationship highly with a coefficient of 0.583 ($z = 3.972$, $p < 0.000$), meaning it plays a part in refining the impact of automation on decision competence.

Table 6: Path Analysis

	OIM Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Attitudes towards automated decision making significantly influences the production efficiency.	0.620	0.050	9.474	0.000	0.521	0.712
Decision making competence significantly influences the production efficiency.	0.679	0.048	10.888	0.000	0.585	0.614
Decision making competence significantly mediates the relationship of attitudes towards automated decision making and the production efficiency.	0.668	0.053	9.736	0.000	0.564	0.612
Big data and predictive analytics significantly moderate the relationship of attitudes towards automated decision making and the decision-making competence.	0.661	0.052	9.790	0.000	0.559	0.756
Problem solving decision making significantly moderates the relationship of attitudes towards automated decision making and the decision-making competence.	0.583	0.206	3.972	0.000	0.346	0.462

5. Discussion

The findings of this research provide a comprehensive understanding into the interface between ADM's impact on production efficiency, with key insights being drawn from the interplay between attitudes, decision-making competence, and external moderating factors such as big data, predictive analytics, and problem-solving skills. Therefore, as industries increasingly begin to rely on automation as a driver to improve operational efficiency, it is increasingly important to understand the behavioral and cognitive impacts on the success of ADM in determining the success of automation solutions. All of these hypotheses in this study being accepted attest to the fact that such variables are significant factors in determining the fruits of production and, therefore, bringing home to people once again the crucial role attitudes and competencies of decision-makers play in optimizing the effectiveness of ADM. It further goes on to point out how the integration of advanced technological tools such as big data and predictive analytics with the problem-solving capability of a good decision-maker amplifies ADM benefits pertaining to improving the efficiency of production. In the course of this chapter, we review these findings at length, taking into account implications for theory and practice as well as more general contributions to extant literature.

The first hypothesis under investigation is that, generally speaking, ADM attitudes do affect production efficiency. Previous research has shown that adopting new technologies and integrating them into workflows is facilitated by favourable attitudes towards them. On the other hand, results show that organizations where decision-makers have positive attitudes toward ADM are marked improvements in efficiency in terms of production because such attitudes can lead to a higher level of acceptance and use of the technology. This follows that of TAM, where how helpful a technology is and how simple it is to use are said to dictate how technology is adopted; such is the view of (Caputo et al., 2023). A decision-maker who perceives ADM positively is more likely to exploit the capacities at hand. The potential of an optimized production schedule and reduced downtime, and the fact that resources are utilized in an efficient manner, would mean that this relationship suggests that improvements in organizational culture around automation with training or leadership can improve the production outcome further. Attitudes towards technology are decisive to determine how effectively an organization can make use of automation tools, as has been suggested by earlier research, and the findings of the present study endorse the premise in the domain of ADM and production efficiency.

Confirmation of the second hypothesis-that decision-making competence impacts significantly upon the production efficiency-deals a further blow to the importance to be held for both cognitive and strategic decision making competencies which could make the ADM process more effective. The results indicate that the quality of competence determines a competent decision-maker's capability in decision-making that is as timely as it is informative enough in order to maximize the returns from ADM, especially when the production environment requires complex production and tools for automation call for constant monitoring and even adjustments to come out efficiently. Competent decision-makers can interpret the data that is generated by ADM systems to troubleshoot as well as make decisions in real-time in order to boost their operational efficiency. It is backed up by empirical studies, as improvement in decision-making competence leads to better results in production (Sharma & Villányi, 2022), more especially if the issue of technology is concerned with the environment. The results are also consistent with Srioguz and Miser (2024) findings that decision-making competence as far as cognitive abilities are concerned in making good decisions if the conditions were uncertain. As ADM systems continually process and respond to vast amounts of data in the production environment, decision-making competence implies that, for the decision-makers, these ADM systems can be navigated with an efficiency maximized through decision-making competence.

Acceptance of the third hypothesis that proposed "attitudes toward ADM are mediated by production efficiency through decision-making competence" offers excellent insight into the role that decision-making skills can play as a bridge between attitudes and resultant operational outcomes. Thus, the results indicate that positive attitudes are insufficient to drive important improvements in production efficiency; rather competent decision-making ability is the prerequisite that transforms these attitudes into effective action. This mediatory effect indicates that organizational efforts should not be predominantly focused on creating positive attitudes towards ADM but should also build the decision-making competencies of their employees. This is supported by more general technology adoption and decision-making literature, which underlines that there is a need for specific cognitive skills to harness the true benefits of automation tools (Bickley et al., 2024). In this study, having a positive attitude of ADM toward the decision-makers, the higher skills level would enhance their capabilities to put that attitude into practice. Such an effective production strategy led to productivity improvement. This mediation further underlines the excellence of training programs that are, instead of only supposed to load the workforce with technological literacy, also supposed to make it strategic in its nature.

The fourth hypothesis, which focused on the moderating role of big data and predictive analytics (BDPA) in the relationship between attitudes towards automated decision-making and decision-making competence, was also supported by the data. The findings suggest that BDPA strengthens the link between positive attitudes towards automation and decision-making competence. When employees are equipped with predictive analytics tools, they are more capable of making informed and effective decisions, particularly in automated environments (Virmani et al., 2024). This points to the importance of integrating BDPA into decision-making processes to enhance the ability of managers and engineers to interpret automated outputs and make strategic decisions, ultimately leading to better organizational performance.

The fifth hypothesis explored the moderating effect of problem-solving decision-making on the relationship between attitudes towards automated decision-making and decision-making competence. The results reveal that employees who possess strong problem-solving skills are better able to translate their positive attitudes towards automation into competent decision-making. Problem-solving serves as a crucial cognitive skill that enables individuals to navigate the complexities of automated systems, identifying challenges, and implementing effective solutions (Nilashi et al., 2023). The interaction between problem-solving decision-making and attitudes towards automation suggests that employees who are proficient in problem-solving can maximize the benefits of automation, as they can better address the issues that may arise in automated environments and adapt to changing circumstances efficiently.

In conclusion, the findings of this study validate all five hypotheses, emphasizing the intertwined roles of attitudes towards automated decision-making, decision-making competence, and production efficiency. Decision-making competence was identified as a key mediator, while both BDPA and problem-solving decision-making emerged as significant moderators in enhancing this relationship. These results offer valuable implications for organizations aiming to improve production efficiency through automation. By investing in decision-making training, fostering problem-solving skills, and utilizing big data and predictive analytics, companies can ensure that the implementation of automated systems is both efficient and effective, leading to improved production outcomes. The study contributes to both theoretical and practical knowledge, providing a comprehensive understanding of the factors that influence the success of automation in the workplace.

6. Implications of the study

This paper greatly contributes to the theoretical understanding of ADM and its contribution to the efficiency of production because it brings forth decision-making competence, big data analytics, and problem-solving decision-making as key moderating and mediating variables. Drawing from existing theory, such as the TAM and Decision-Making Theory, it pushes the discussion forward in how attitudes toward ADM interact with individual competencies and organizational data capabilities in enabling superior production outcomes. This robust support by the findings to the mediating role of decision-making competence in strengthening the relationship between ADM attitudes and efficiency shows that indeed, competence in the decision-making process is critical in translating technological attitudes into practical benefits. From this angle, the reader will also discover that big data and problem-solving decision-making present an even more defined view as to how organizations can make the most out of these tools to amplify ADM system benefits: complete in terms of offering a holistic view which further develops theoretical models in decision sciences as well as production management.

From a practical point of view, the results of this research are going to guide management and organizations on how to enhance the efficiency of production through the use of ADM systems. Employees have to develop positive attitudes favorably disposed towards ADM; as shown earlier, attitudes determine outcomes for production; thus, there is a need for training and more powerful communication strategies to create trust in ADM technologies. Technology-enabled targeted skill development programs for improving employee's decision competence will be maximized through ADM technologies because, according to this study, it has been revealed that competence is a mediator of the relationship between attitude towards ADM and efficiency. Additionally, enhancement in the application of big data analytics and integration of problem-solving decision-making can be strategic tools to enhance production efficiency further more. It would imply that to implement ADM, both technological capabilities and human factors need to be worked upon, such that employees are fully comfortable with ADM technologies but can also decide on informed choices through making the proper use of predictive analytics toward improvements in operational performance.

7. Limitations and Future Research Directions

Although these are the contributions of this study, there are some limitations that can call for further exploration. Since this study zeroes in on focusing the production efficiency of a particular industry, findings could not be generalizable to other areas or sectors. Future work may contemplate different diversified industry impacts of ADM on efficiency, such as healthcare, education, or finance, to increase the applicability of the results. This study provides further strengths by considering, as a mediating variable, the decision-making competence but does not take into account other possible mediators such as organizational culture or leadership styles that may also affect the relationship of ADM efficiency. Future research studies could consider such factors in order to build a more complete perception of ADM effectiveness drivers. Last but not the least, this study sets the ground open for further research into possible risks or challenges thrown up by the emergence of ADM, such as overdependence on technology or reduced human oversight in critical decision-making.

Another limitation is the cross-sectional design, which collects data at a single point in time. These kinds of designs restrict the estimation of changes in attitudes towards ADM, competence to decide, or outcome efficiency over time. Future study designs will have to utilize longitudinal approaches tracing how such variables change within time, which would give more dynamic insights into how systems of ADM influence production efficiencies over longer periods of time. It also presents the need for big data and predictive analytics while not fully unfolding the role of different types of data or the specific analytical techniques that may further optimize decision-making. The third concern with respect to the future of ADM systems refers to the potential use of advanced analytics methods, such as machine learning or artificial intelligence, as opposed to more traditional sophisticated methods. That could increase the impact of ADM systems on efficiency, but the impact would be very granular in nature as well as the production environments data-driven approaches might support.

8. Conclusion

Finally, this study makes a crucial point about the role that automated decision-making can play as an adjunct to increasing production efficiency, with decision-making proficiency serving as a crucial middleman. The findings demonstrated that while optimistic views regarding automation are highly effective, they must be supported by skilled ability to make decisions in order to result in significant increases in productivity. Thus, a gap has been quite vividly revealed between attitudes and outcomes, which makes the role of decision-making competency a pivotal one in that sense, establishing the necessity of embedding employee development in addition to applying automation technologies. The use of big data and predictive analytics as a moderator strengthens this association between attitudes towards automation and decision-making competency and underlines the need of incorporation of BDPA tools into the ecosystem of decision-making. Further, the moderating effect of problem-solving decision-making shows that employees with strong problem-solving skills are more viable for the realization of benefits from automation. Such employees can navigate the complexities of automated systems with better efficacy and will ensure that overall organizational efficiency benefits from automation. This study not only enhances the existing literature on automation and decision-making but also gives practical implications in the confectionery industry and beyond. The integration of a mix between decision competence, BDPA, and problem-solving skills unlocks better productivity and efficiency by organizations.

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Appendix 1

Attitudes towards Automated Decision Making

1. Implementing automated decision-making in production scheduling will save on costs.
2. Using automated systems for production decision-making will be more objective.
3. Automated decision-making in production is biased and unfair.
4. Risk scoring through automation will help prevent errors in production processes.
5. Error prevention in production will be easier and more efficient with automated decision-making.
6. Factories that comply with regulations may be falsely flagged by automated systems.
7. The use of AI for product quality recognition is a good way to prevent defects.
8. Production issues identified using AI should always be thoroughly investigated.
9. If production errors are wrongly identified by automated systems, they should be corrected promptly.

Decision Making Competence

1. My production-related decisions are knowledge-based.
2. My decision-making in production is consistent across shifts.
3. I consider uncertainty and unknowns in my production decision-making approach.
4. I generate a SWOT analysis when making decisions about production efficiency.
5. I present contingencies or achievable options when making production decisions.
6. My decision-making process in production is transparent to my team.
7. I understand the context of the decisions I am being asked to make in production.
8. I understand the importance of the production decisions I make.
9. I use a structured approach to decision-making in production management.
10. I qualify the probability of success when making production-related decisions.
11. I quantify the probability of success when making decisions related to production efficiency.
12. I receive training in decision-making science for production management.
13. I use intuition or "gut-feeling" when making production-related decisions.
14. My professional experience is important when making challenging production decisions.

Big Data and Predictive Analytics (BDPA)

1. Our factory intends to adopt BDPA for optimizing production in the future.
2. Our factory recommends the use of BDPA to other companies in the industry.
3. Our factory follows the required strategies for the effective utilization of BDPA in production.

Problem Solving Decision Making

1. Diagnosis: Who should determine (diagnose) the likely causes of production inefficiencies?

2. Options: Who should determine what the options are for addressing production inefficiencies?
3. Risks and Benefits: Who should determine the risks and benefits of each option for improving production efficiency?
4. Probability: Who should determine how likely each of these risks and benefits is to happen in the production process?
5. Utility: Given the risks and benefits of possible solutions, who should decide how acceptable those risks and benefits are for production?
6. Action: Given all the information about risks and benefits of possible solutions, who should decide which option should be implemented to optimize production?

Production Efficiency

1. How do you rate the current level of production efficiency in your factory?
2. Product design has a significant impact on the current level of production efficiency in the factory.
3. Process design significantly influences the current level of production efficiency in the factory.