

Digital Literacy and Big Data Analytic Tools in Economic Policy Formulation: A PLS-SEM Analysis

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ABSTRACT

Big Data Analytics (BDA) tools are becoming increasingly important for evidence-based economic policy-making to monitor economic activity and make informed decisions. But the effective use of tools is contingent on the digital literacy (DL), perceived usefulness (PU) of technology, and implementation challenges. This research investigates the interrelationships between DL, PU, implementation barriers and implementation importance (IM) of BDA tools among economic policy professionals, as well as the mediating effect of PU. A survey of 110 economic policy professionals in Jordan was conducted and tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings show that DL positively affects PU and IM of BDA tools. Similarly, PU positively affects IM confirming the importance of PU in technology acceptance. In addition, DL directly influences IM revealing that there are direct and indirect behavioural mechanisms at play. Moreover, the research reveals that implementation issues have a negative impact on PU (albeit a small one). Mediation tests reveal that PU partially mediates the digital literacy-IM link. The model's explanatory power is adequate, with moderate variance explained (R^2) for the core endogenous variables. Predictive relevance (Q^2) also supports the adequacy of the model, with reliability and validity measures supporting the measurement adequacy. In all, the results identify DL as a major predictor of BDA adoption in economic policy making, while PU serves as an important psychological construct that converts capability into commitment to adoption. This research adds to the technology adoption body of knowledge by incorporating both behavioral and capability approaches in the realm of data-driven governance and economic policy.

Keywords: Big Data Analytics, Digital Literacy, Perceived Usefulness, Implementation Challenges, Structural Equation Modeling

JEL Classifications: D78, H11, O33

1. INTRODUCTION

The growing intersection of digital transformation and BDA in government has significantly transformed policy formation, design, and assessment in economic affairs. In the policy arena, the use of BDA has facilitated a transition from responsive to anticipatory decision-making, allowing governments and financial institutions to harness big data for macroeconomic monitoring and strategic planning (Fattah, 2024; Ahmed, 2023). This transformation is particularly important in developing countries like Jordan, where structural problems including low economic growth (around 2-3% GDP), budget deficits, and a high unemployment rate (over 20%) create a need for more effective and informed policy-making

(Baig et al., 2023; Gupta and Jaiswal, 2025). In this ever-changing environment, the DL of economic policy practitioners has become a critical factor in facilitating the adoption of BDA, influencing both the technical and strategic views on its value and application. DL, as a multifaceted construct that combines technical, cognitive, and analytical skills, plays a pivotal role in facilitating interactions with complex data environments (Guillén-Gámez et al., 2023; Jayashree et al., 2026). In policy settings, it goes beyond basic information and communication technology (ICT) skills to encompass the skills of critical evaluation of data sources and interpretation of results produced by algorithms, and ethical issues such as data privacy and data bias (Meutia et al., 2025; Ly, 2025). The choice of DL as a key independent variable aligns with technology acceptance

and human capital theories, which stress the importance of user skills in the adoption of technological innovations (Ibrahim and Aduah, 2025). Similarly, PU – the extent to which policymakers believe BDA tools improve policy outcomes – remains a key predictor of technology adoption and is validated across various technological applications (Davis, 1989). Perceived IM is also factored into this study to reflect the institutional prioritization of BDA, and therefore the degree to which policymakers see these tools as critical for long term governance (Nurfaizal et al., 2025).

Crucially, implementation challenges are also incorporated to temper the enthusiasm for digital transformation. These challenges, including data governance, infrastructural, algorithmic, and regulatory challenges, have been demonstrated to play a moderating role in the perceived benefits of advanced analytics (Rahimi and Mosalli, 2025; Saeed et al., 2025). Furthermore, this model includes data-processing needs to account for the technological readiness and infrastructural capabilities needed to implement BDA systems, especially in settings where digital ecosystems are still in the making (Ahmed, 2023; Ullah et al., 2025). Together, these variables constitute a holistic representation of enablers and constraints on the adoption of BDA in economic policy. Jordan is a natural empirical focus because of its digital transformation in several sectors, such as banking, telecommunications and government. The banking sector, a key contributor to GDP, has embraced sophisticated analytics for credit risk management and financial inclusion policies. Likewise, the telecommunications sector, with its high mobile penetration (over 80%), uses big data for segmentation and service provision. Government efforts, including e-government services, also demonstrate the embrace of digital technologies. These industries were chosen based on their data-intensive nature, economic importance and their involvement in digital technologies, providing suitable environments to study the interaction of DL and BDA adoption (Jayashree et al., 2026; Ullah et al., 2025). Although there is an increasing number of studies on big data and technology adoption, there are still some important gaps. Much of the literature concentrates on developed countries, with a lack of evidence from emerging markets like Jordan (Khabibi and Purnomo, 2026; Williams et al., 2024). Existing studies tend to focus on organizational capabilities and overlook the importance of individual-level skills, such as DL (Abd Jalal et al., 2023; Fattah, 2024). Most research employs piecemeal analytical frameworks that do not include PU, IM and challenges in a single structural framework (Novela et al., 2024; Ly, 2025).

Regulatory and ethical issues are often considered as control variables, despite increasing concerns about data governance (Bilal et al., 2026). Other gaps include sector-specific research (Saeed et al., 2025), inadequate focus on data-processing infrastructure (Hongyun et al., 2025), a lack of mediation analysis (Williams et al., 2024), under-representation of the public policy perspective (Guo and Shen, 2024), limited attention to real-time analytics (Ly, 2025), and insufficient investigation of institutional factors in emerging economies (Jayashree et al., 2026). Overcoming these gaps requires a holistic, contextual, multidisciplinary approach that considers behavioral, technological and institutional factors. As such, the research questions for this study are: (RQ1) How does economists' DL impact their view on the PU and IM of

BDA? (RQ2) How do implementation issues affect PU of BDA in economic policy-making? (RQ3) Is there a mediation effect of PU on DL and IM? These questions aim to capture both direct and indirect effects of influence and provide a comprehensive view of technology adoption. This study has four goals: to understand the effects of DL on PU and IM; to test the effects of implementation challenges on PU; to test the mediating role of PU; and to test the importance of data processing needs on perceptions of adoption.

Through the use of PLS-SEM analysis based on primary data from economic policy experts in Jordan, the research adopts a rigorous and relevant approach. This research is important due to its holistic and multi-dimensional approach. Theoretically, it builds on the TAM to include DL and policy-specific contextual factors. In terms of practice, it offers practical recommendations for policymakers, central banks and financial institutions to improve their data analytics skills. The research has a wide range and focuses on cross-sectoral digital transformation in the economy. It is unique in its approach to synthesising human capital, technological readiness, and institutional challenges. Driven by the pressing need for evidence-based policy in developing countries, this study adds to the academic conversation and practice by providing a strong empirical model for understanding the adoption of BDA. Finally, it fills important gaps in the literature and sets the stage for future work on the digital transformation of policy, highlighting the pivotal role of digital literacy in the future of economic policy-making.

2. THEORETICAL BACKGROUND

This study builds on an integrated theoretical approach that draws on the Technology Acceptance Model (TAM), the Resource-Based View (RBV) and Human Capital Theory (HCT) to holistically account for the use and PU of BDA tools in economic policy settings. The choice of theories is strategic and synergistic, as they offer complementary perspectives on the role of DL, PU, IM and institutional challenges in the context of data-driven governance. The TAM is the main theoretical framework used in this study. Davis (1989) first introduced TAM, which suggests that PU and perceived ease of use are key factors influencing technology use. In this study, PU is maintained as a key construct, as it has been empirically supported across various technology contexts (Guillén-Gámez et al., 2023; Aziz et al., 2024). The incorporation of perceived IM into TAM aligns with the shifting landscape of technology adoption in institutional contexts, where the importance of strategic priority and policy fit is paramount (Bilal et al., 2026; Hidayat-ur-Rehman, 2025). Furthermore, the addition of challenges to implementation aligns with recent critiques of TAM, which advocate for the inclusion of contextual and risk factors to better understand technology adoption (Ibrahim and Aduah, 2025; Khabibi and Purnomo, 2026). The consistent findings of empirical studies that PU mediates the impact of individuals' competency on adoption intentions, justify its inclusion as a mediator in the current study (Ahmed, 2023). The HCT theory supports the inclusion of DL as an independent variable, complementing TAM. HCT suggests that individual knowledge, skills and competencies play a vital role in enhancing productivity and innovation (Becker, 1993; Schultz, 1961). In

the BDA context, DL is a type of human capital that empowers individuals to interact with data systems, draw meaningful conclusions and take informed actions (Gupta and Jaiswal, 2025). Existing research has found a positive link between digital skills and technology adoption, especially in knowledge-based settings (Ibrahim and Aduah, 2025; Waqar and Paracha, 2024). Additionally, studies suggest that increasing digital literacy skills not only leads to increased PU but also confidence in the use of advanced technologies in the workplace (Jain et al., 2024). This theory provides strong theoretical support for the direct and indirect influences of DL on the study's model. The resource-based view (RBV) also enhances the theoretical underpinning of the study by highlighting the strategic value of resources and capabilities in gaining competitive advantage (Barney, 1991). In this research, BDA tools and data processing capabilities are defined as strategic resources, and DL is considered as a human resource that facilitates the use of these resources. RBV supports the inclusion of data-processing needs as a variable because the availability and integration of the technological infrastructure play a critical role in the adoption of analytics (Fattah, 2024; Hidayat-ur-Rehman, 2025). Furthermore, challenges in the adoption of big data technologies, including data privacy, regulatory restrictions and infrastructural limitations can be seen as factors that prevent effective resource deployment (Kalsum et al., 2025; Rîndaşu et al., 2023).

The empirical literature has also shown that firms with effective data resources and capabilities, as well as human resources, are more likely to benefit from big data projects, thereby also highlighting the importance of RBV (Nurfaizal et al., 2025). The combination of the theories provides a holistic and multi-dimensional perspective, addressing both individual and organizational factors influencing BDA. TAM addresses the psychological aspects of technology acceptance, HCT emphasizes the importance of individual skills, and RBV offers insights into the strategic and infrastructural factors. This triangulation overcomes the constraints of single-theory models and is aligned with recent calls for more integrated frameworks in the study of technology adoption (Miraz et al., 2025; Ullah et al., 2025). This multifaceted approach is supported by a growing body of evidence that highlights the need for a multifaceted approach to technology adoption. For example, Jayashree et al. (2026) and Novela et al. (2024) stress the disruptive role of big data in decision making, but also the importance of human capital. Likewise, Ibrahim and Aduah (2025) and Soomro et al. (2024) show that data skills and capabilities improve organisational performance, especially when combined with analytical skills. Ly (2025) and Rahimi and Mosalli (2025) also underline the impact of institutional and implementation aspects on technology adoption. In addition, Waqar and Paracha (2024) emphasise the increasing importance of ethical concerns including data privacy and algorithmic transparency in shaping user perceptions and trust. In the emerging market economies, Hidayat-ur-Rehman (2025) and Meutia et al. (2025) demonstrate that institutional factors and resource constraints play a vital role in the adoption of digital technologies, highlighting the need for locally relevant studies. Furthermore, the research of Waqar and Paracha (2024) empirically supports the mediation of perceived usefulness, and Rahimi and Mosalli (2025) emphasize the

importance of data infrastructure in facilitating analytics adoption. The studies reviewed offer robust empirical evidence in support of the model and its theoretical premises. Overall, the theoretical basis of this study is both holistic and contextual, drawing on TAM, HCT and RBV to understand the dynamics between PU, IM, DL, implementation challenges and data processing needs. Such a combined approach not only enhances the model's explanatory capacity but also lays the groundwork for future research on the adoption of BDA in economic policy-making, especially in emerging economies like Jordan.

2.1. Hypothesis Development

Our proposed link between DL and PU is premised on the growing sophistication of data-driven policy-making, in which fluency in interpreting, analysing, and using vast quantities of data is critical for decision-making. DL, defined as the integration of technical, cognitive and analytical skills, allows economists to interact effectively with sophisticated analytical technologies, as well as extract insights from complex data ecosystems (Aziz et al., 2024). Within the framework of BDA, higher DL is more likely to facilitate an understanding of the capabilities of these technologies, leading to increased PU in policy analysis and forecasting (Bilal et al., 2026). Theoretically, the TAM suggests that PU is a key factor influencing the adoption of technology, and this perception is influenced by users' existing knowledge and skills (Rahimi and Mosalli, 2025). This relationship is also supported by empirical evidence, showing that users with high DL demonstrate greater PU when they use data-driven technologies (Jain et al., 2024). In policy settings where evidence-based and rigorous approaches are critical, digitally literate economists are more likely to appreciate the strategic significance of BDA tools in improving policy quality and responsiveness (Gupta and Jaiswal, 2025). Thus, this research proposes that DL plays a positive and significant role in economists' perceptions of BDA usefulness, further entrenching its importance in technology acceptance in economic governance.

- H_1 : Economists' DL positively influences their PU of BDA tools in economic policy formulation.

The link between PU and IM is founded on the idea that technologies perceived to be useful are more likely to be prioritised for institutional integration and strategy implementation. Within the realm of economic policy making, PU translates into economists' assessments of the ability BDA tools to improve decision-making accuracy, forecasting and evidence-based policy making. The greater the recognition among policymakers that BDA tools enhance effectiveness and policy outcomes, the more likely it is that policymakers view implementation as critical (Soomro et al., 2024). This connection is well supported by the TAM, which asserts that PU is a key predictor of behavioural intention and system use, especially in workplaces and organisations (Fattah, 2024). In the policy context, implementation importance can be construed as a strategic expression of behavioral intention, as PU translates into institutional prioritization (Aziz et al., 2024). Additionally, empirical evidence suggests perceived value in using advanced technologies to enhance performance is more likely to be promoted at the corporate and policy levels (Ibrahim and Aduah, 2025). In data-driven governance environments where real-time

information is crucial, PU of BDA tools is a key factor in influencing its adoption in policy environments (Hidayat-ur-Rehman, 2025). Thus, it is theoretically and empirically reasonable to assume higher PU result in higher perceived importance of adopting BDA tools for economic policymaking.

- H_2 : The PU of BDA tools positively affects the perceived importance of their implementation in economic policy processes.

The positive influence of DL on perceived IM stems from the recognition that those with greater digital literacy are more likely to appreciate the strategic potential of emerging technologies in organisations. DL, which includes analytical reasoning, data interpretation, and technical skills, enables economists to effectively employ BDA tools and understand the wider impact on efficiency and innovation in policymaking (Guo and Shen, 2024). Consequently, digitally competent workers are more likely to champion the role of BDA in economic policy-making, viewing it as essential for evidence-based policy (Soomro et al., 2024). Theoretically, HCT assumes that individuals with higher skill levels can contribute more to organisational performance and are more open to adopting new practices (AlNuaimi et al., 2021). Here, DL is a valuable resource that endows economists with the knowledge to analyse and prioritise investments in technologies. Also, empirical evidence affirms that people with higher digital skills show greater support for the adoption of new technologies in their organizations (Basit et al., 2025; Ibrahim and Aduah, 2025). Furthermore, in a policy-making context that increasingly relies on data analytics, understanding and trusting the analytical results impact perceptions of the need for implementation (Ullah et al., 2025). Consequently, economists with higher DL can not only effectively operate BDA but also perceive their implementation as critical for their strategic goals, hence, the positive direct link proposed here.

- H_3 : Economists' DL directly and positively influences the perceived importance of implementing BDA tools in economic policymaking.

The link between implementation challenges and PU stems from the recognition that perceived implementation challenges can erode trust in the perceived effectiveness of technological systems. In terms of BDA, while the benefits of using these tools may be high, practical limitations such as a lack of infrastructure, computing power and technical skills may limit economists' ability to achieve these benefits (Hongyun et al., 2025). Likewise, privacy concerns and algorithmic biases can create distrust in the data and analyses generated, reducing PU (Ly, 2025). Theoretically, the TAM acknowledges PU is influenced by external factors that affect users' perceptions of system performance (Fattah, 2024). At higher levels of implementation challenges, users are less likely to view the system as valuable or effective because they see the challenges as outweighing the benefits (Gupta and Jaiswal, 2025). In public sector and policy settings, these challenges may be more severe given bureaucratic and resource limitations, which ultimately affect trust in advanced analytics systems (Jain et al., 2024). This negative association is also supported by empirical evidence,

revealing that technological, organizational and institutional challenges play a crucial role in limiting the effectiveness of data-driven systems (Nurfaizal et al., 2025). In emerging markets like Jordan, such challenges are more important as digital infrastructure is uneven and few receive advanced analytics training (Saeed et al., 2025). Hence, it is theoretically and empirically supported that greater implementation challenges impact the PU of BDA tools of economists in economic policymaking.

- H_4 : Implementation challenges (e.g., data privacy concerns, regulatory constraints, infrastructural limitations, and lack of technical expertise) negatively affect the PU of BDA tools in economic policy formulation.

This hypothesis is premised on the idea that DL does not directly lead to prioritization of implementation unless it first influences the users' cognitive appraisal of the usefulness of a technology. Here, PU serves as an important psychological mechanism by which DL affects the prioritisation of adopting BDA. Economists with greater DL have a greater ability to comprehend, analyse and use different data sets and this enhances their perception of the value of BDA tools in increasing the accuracy and efficiency of their policy decisions (Basit et al., 2025). This improved understanding of usefulness, in turn, results in a higher appreciation of the need for adopting such tools in economic policy-making. The mediation theory is well supported by the TAM, which identifies PU as the key factor that bridges external factors (such as user skills) with usage intentions and adoption behaviour (Ullah et al., 2025). Building on TAM, previous studies have shown that user abilities and computer skills are often indirectly related to technology adoption via cognitive appraisal factors such as usefulness and performance expectancy (Ibrahim and Aduah, 2025; Ali, 2026). This suggests that DL might not directly influence implementation priorities unless it contributes to positive appraisal of PU. Similarly, empirical research supports this indirect effect in technology adoption, demonstrating that PU plays a significant role in passing on the influence of individual skills to technology adoption intentions (AlNuaimi et al., 2021). In data-driven policy settings, economists who perceive BDA tools as useful may be more likely to recommend institutionalizing and prioritizing their use in decision-making (Ibrahim and Aduah, 2025). Hence, it is reasonable to assume PU as a mediating variable, clarifying the effects of DL on enhanced perceptions of IM in economic policy-making environments.

- H_5 : The relationship between economists' DL and the perceived IM of BDA tools in economic policymaking is mediated by PU.

2.2. Cultural and Geographic Considerations

Geographical and cultural contexts are key in determining the uptake, perception and successful use of BDA tools in economic policy domains. In developing economies like Jordan, these factors have a significant impact on account of differences in institutional development, digital infrastructure, and socio-cultural acceptance of technology use in decision-making (Fattah, 2024). Unlike mature economies that have deeply ingrained data-driven cultures within institutional decision-making, in

emerging markets, transitional digital economies tend to co-exist with traditional decision-making methods (Saeed et al., 2025). Culturally, factors such as organizational innovativeness, uncertainty avoidance and decision-making hierarchy play a role in technology adoption. Cultures with high uncertainty avoidance may show aversion to data-driven governance systems because of perceived risks in using algorithms to support decision-making and the loss of human judgment (Jain et al., 2024). Here, even if digital solutions are accessible, their PU may be mitigated by trust concerns, institutional inertia, and a bias towards human judgement over algorithmic suggestions (Hongyun et al., 2025). Culture thus plays a vital role in the views of economists towards the use of BDA in policy making. From a geographical perspective, Jordan is a strategically located emerging economy in the Middle East with moderate levels of digital transformation, but infrastructural and economic challenges. Jordan has heavily invested in e-government, fintech and ICT development; however, digital maturity varies among institutions and economic sectors (Ali, 2026). For example, the telecommunications and financial sectors are relatively advanced in terms of digital readiness, but challenges in data integration, interoperability and human resource capacities are still evident in the public policy sector (Gomes, 2025). These spatial and sectoral differences have a direct impact on the perceived potential and feasibility of BDA among economic policy practitioners. Additionally, economic conditions, including employment dynamics, budget deficits, and reliance on foreign aid and loans, influence the need for sophisticated analytical platforms. Jordan, with unemployment rates above 20% and low economic growth rates, is under pressure to adopt evidence-based policies to enhance efficiency and resource allocation (Ahmed, 2023). But the success of these strategies depends on the availability of DL and institutional cultures conducive to data-driven governance (Ibrahim and Aduah, 2025). Previous studies have stressed that the use of the technology is not only a technical process but also social and cultural (Basit et al., 2025). Basit et al. (2025) and Gupta and Jaiswal (2025) reveals that the institutional settings of developing world often limit the effective adoption of digital technologies despite their benefits. Likewise, Jayashree et al. (2026) suggest that regional preparedness and readiness, IT infrastructure and cultural adaptability play a crucial role in big data projects. These studies underline the need to consider cultural and geographical factors in models of technology acceptance, especially in areas sensitive to policy. In this study, Jordan's socio-economic context offers a pertinent and underresearched setting in which to examine the adoption of BDA in economic policy. The overlap of modern digital programs and traditional bureaucratic frameworks generates a "mixed" environment where attitudes towards usefulness and IM are likely to be influenced by both technological and cultural factors. So, incorporating cultural and geographical factors adds to the predictive value of the study's model and allows a more sensitive approach to understanding the digital transition in economic governance.

3. METHODOLOGY AND DATA

In this paper, we used the PLS-SEM method for data analysis. It has been shown to be a convenient and robust method in research (Hair et al., 2017) and is suitable for testing new theoretical models

in new areas (Hongyun et al., 2025). PLS-SEM was selected due to the small sample size ($n = 112$) and it is suggested in the literature for smaller sample sizes (Hair et al., 2017). Moreover, the PLS-SEM approach facilitates the testing of mediation in the model, and does not assume a particular data distribution (Fattah, 2024). The analyses were conducted using SmartPLS 4.1.0.8. Data was collected in line with the ethical guidelines from the Norwegian National Research Ethics Committees and approved by the Norwegian Centre for Research Data (SIKT) with project number 812,457. We obtained informed consent from all respondents before they completed the questionnaire, and anonymous action procedures were applied to ensure privacy of the respondents, as per GDPR regulations. According to the Taylor and Francis AI guidelines, this manuscript was written using ChatUiT (chat.uit.no).

3.1. Measurement Instrument

The scales used in this study were adapted from prior studies of technology acceptance and implementation of economic policy analytics. The measurement scales for the DL and PU constructs were based on the scales developed by Davis (1989) in his research on technology acceptance in the workplace and policy. The items for measuring the IM were developed based on frameworks for measuring technology acceptance in professional and policy contexts, as discussed in the TAM. The measurement of implementation challenges was developed using constructs that are widely used in information systems research to capture infrastructural, technical and regulatory barriers that impact adoption. The items for assessing data-processing needs were constructed based on well-developed criteria for computing infrastructure readiness and analytics capability needed to support BDA, as identified in previous empirical studies on BDA adoption.

3.2. Variable Construction

Based on the hypotheses developed, four latent variables were constructed as reflective constructs, following the guidance by Hair et al. (2017): DL, which captured respondents' awareness and familiarity with BDA tools for policy-making in economics (three reflective indicators); PU, which measured respondents' views on the usefulness of BDA (four reflective indicators); IM, which captured respondents' perception of the importance of using BDA tools in economic policy-making (three reflective indicators); and Implementation_Challenges, which evaluated perceived challenges of BDA implementation (five reflective indicators). All variables were measured on 5-point Likert scales, with different anchors for each construct (from "Not much" to "Very much" for DL, from "Strongly Disagree" to "Strongly Agree" for PU, from "Not important" to "Very important" for IM and from "Not significant at all" to "Very significant" for Implementation_Challenges). Details of the measurement items are in the Appendix A.

3.3. Sample and Data Collection

A questionnaire was developed to gather data. Given the research questions, the research respondents were employees of economic and policy institutions in Jordan, namely economists, policy analysts and economic policy researchers. Given the need to access respondents who are spread throughout the country, the

survey was administered electronically, through the Nettskjema website (nettskjema.no). In this study, a non-probability sampling was used, as the questionnaire was distributed to accessible e-mail addresses. The questionnaire was distributed to more than 500 public e-mail addresses of the institutions within Jordanian economic and policy sector. Data were collected from the end of December 2025 to the end of January 2026. During the data collection period, 110 questionnaire responses were given. Responses to the questionnaire came mainly from Jordan's central government institutions (72 responses), and financial regulatory agencies (28 responses), as shown in Figure 1. There were also responses from research institutes (5), institutions in the banking sector (4) and policy advisory institutions (3). The sample has a larger number of respondents from public institutions (85) than private institutions (27). The sample is dominated by respondents from ministries or other national institutions (76). The remaining respondents were from a range of economic research centers (24), financial institutions (9) or other institutions (3).

As shown in Figure 2, most respondents (83) were economists or policy analysts. There were also 15 researchers, 8 administrators and 6 respondents from other jobs in economic policy institutions. The sample was balanced in terms of the respondents' work

Figure 1: Distribution of respondents by institution type (Jordan)

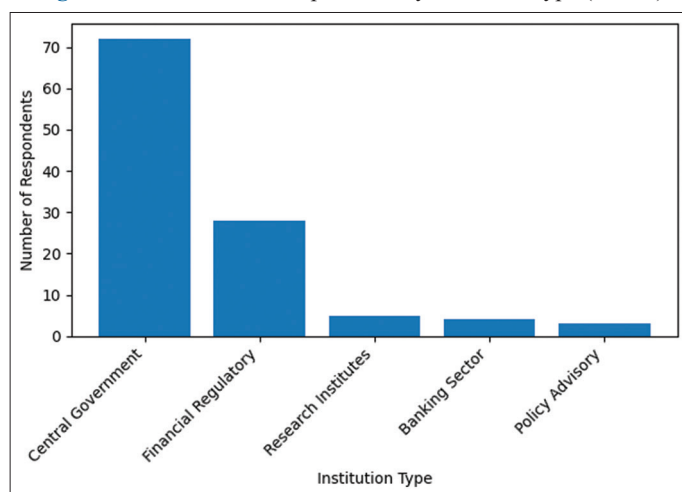
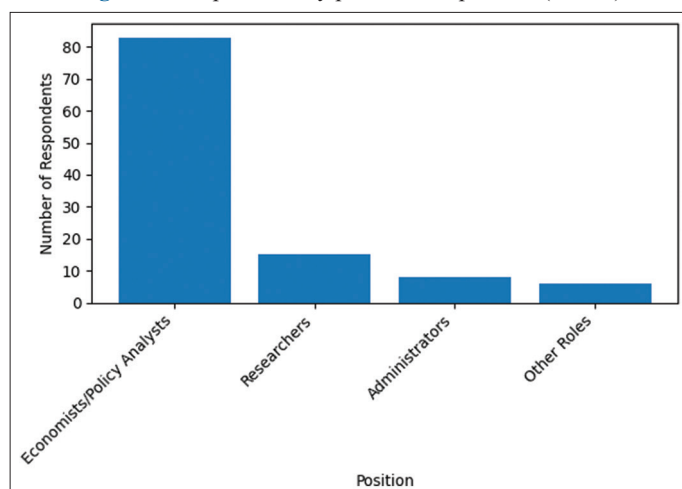


Figure 2: Respondents by professional position (Jordan)



experience. We had 38 respondents with <5 years of experience, 46 with 5-10 years of experience and 28 with experience of more than 10 years. Our research offers insights into the DL of economists and their attitudes towards BDA tools, but it is essential to highlight some of the limitations. First and foremost, the survey used non-probability convenience sampling, which limits the ability to draw inferences. Unlike probability-based sampling, non-probability sampling does not offer equal selection probabilities for all members of the population, which may lead to sampling bias and hinder generalizability of the results to the wider population of economic policy professionals in Jordan (Ali, 2026). This method was chosen due to practical challenges such as the lack of availability of sampling frames of economic policy professionals in Jordan and the financial constraints to undertake probability sampling. As a result, the sample may be biased towards more technology-savvy or technologically-interested professionals, as these individuals may be more likely to respond to internet surveys on data-driven policy systems. Second, there may be considerable variation across institutions in Jordan in terms of digital infrastructure and BDA. Variations in technology use across institutions may affect respondents' perceptions and reported DL. Third, in our study, data on DL and perceptions of the system were self-reported rather than measured or assessed directly. This may lead to biases as respondents could over- or underestimate their digital skills due to social desirability bias or lack of perception of their own skill level. Moreover, our study did not account for the actual level of Big Data use in the institutions of respondents, which could influence the generalisation of the results across different institutions. This should be taken into account when analysing the results, as they reflect individual perceptions rather than objective measures that are comparable across all institutions. In future studies, it is recommended that probability sampling techniques be used, if possible, and that self-reported measures be complemented with objective measures of DL and system usage. While these are limitations, the strength of the sample is that it includes respondents from different institutional backgrounds (public/private, government/research/financial institutions), and a high proportion of economists and policy analysts ($n = 83$), who are the key users of BDA tools in Jordan for economic policymaking.

3.4. Multigroup Analysis

A multi-group analysis comparing economists/policy analysts ($n = 83$) with other economic policy professionals ($n = 29$) found no differences in the path relationships of the structural model (path coefficient differences: $\Delta\beta < 0.12$, $P > 0.05$ for all paths). This suggests role type does not affect the relationships among DL, PU and IM. The lack of significant differences in relationships between DL, PU and IM across different job roles indicate the stability of these relationships across different roles within economic policy institutions. This suggests that the model represents underlying features of the acceptance of BDA in economic policymaking that are independent of specific professional roles. This strength justifies the analysis of the entire sample ($n = 110$) rather than just economists/policy analysts to gain a more holistic picture of BDA acceptance in the economic policy field. This insight is significant for the model's applicability to other economic policy roles.

4. RESULTS

The PLS-SEM analysis results indicated that Jordanian economic policy professionals' DL, PU of BDA tools, implementation challenges, and IM of BDA implementation significantly relate to each other. The structural model along with path coefficients and significance levels are shown in Figure 3. This model has a strong explanatory capability as it explains 44% of variance in perceived IM (BDA_Importance) and 31.5% of variance in PU. The results show that all the hypotheses are supported, and that DL is a strong predictor of both PU and IM. There are two steps involved in doing an appropriate PLS-SEM analysis. First, as described in the literature (Hair et al., 2017), the measurement model validity needs to be tested. Then, we can evaluate the structural model and test the structural relationships in the model. The findings of the above steps are presented below.

4.1. Measurement Model Assessment

To acquire indicators for measuring the measurement model in the SmartPLS software, the PLS-SEM algorithm was used (Hair et al., 2017). In this paper, all latent constructs were reflective in the conceptual model that was tested. Consequently, the indicators for the measurement model (that is, the reliability and validity of the model) were the following: factor loadings, Cronbach's alpha coefficient, composite reliability (CR), and average variance extracted (AVE) as it is required in the literature (Meutia et al., 2025). The measurement model testing showed that the construct challenges had low AVE, that is, it could not be deemed as valid ($AVE > 0.5$). This is because the factor loading of one of the items (CH1) was low (0.491), which is less than the recommended threshold of 0.55 by Hair et al. (2017) for a sample of 100 observations. Therefore, CH1 (that is, "High system cost" as a barrier to adopt BDA technologies) was dropped from the model to enhance convergent validity. Following this adjustment, all measures of the adequacy of the measurement model were satisfactory, including the Challenges construct, which now has an acceptable AVE (0.512). No other indicators were dropped. Only CH4 (Resistance to change) demonstrated a lower factor loading (0.642) among the other indicators but a value above the minimum acceptable value of 0.55 suggested by Hair et al. (2017) for a sample of around 100 observations. Furthermore, eliminating the item would undermine the theoretical integrity of the Challenges construct, as resistance to change is a unique

and significant challenge to implementing BDA in economic policy settings as identified in earlier studies (AbdulKareem and Oladimeji, 2024). The choice to keep CH4 is also justified by the fact that the overall AVE of the Challenges construct (0.512) exceeds the minimum threshold of 0.5 after the elimination of CH1, suggesting satisfactory convergent validity for the construct. Table 1 provides the results after removing the bad item. Table 1 shows the reliability and convergent validity results and descriptive statistics for all constructs.

The findings indicate that all scales possess acceptable internal consistency (Cronbach's alpha coefficients range from 0.701 (Challenges) to 0.823 (Implementation_Importance), all of which are above the recommended threshold of 0.6 (Meutia et al., 2025). The PU construct has a mean of 3.871 (SD = 0.142), indicating a positive attitude towards the usefulness of BDA among economic policy professionals, and the DL construct has a mean of 3.604 (SD = 0.021), which suggests an average level of self-reported digital literacy amongst respondents. Reliability of the constructs is confirmed by the values of composite reliability (CR), ranging from 0.805 to 0.891, well above the recommended threshold of 0.6 (Ibrahim and Aduah, 2025). To test convergent validity, we considered factor loadings, average variance extracted (AVE) and the Fornell-Larcker criterion. All factor loadings surpass the minimum acceptable value of 0.55, as suggested by Ullah et al. (2025) for a sample size of around 100, ranging from 0.602 (CH3) to 0.902 (DL3). The largest factor loadings are found in the construct of DL (DL3 = 0.902, DL2 = 0.884), which implies that the items related to the analytical capability and familiarity with software are greatly associated with the construct DL. AVE values for all constructs exceed the threshold of 0.5, with values ranging from 0.512 (Challenges) to 0.735 (IM), indicating good convergent validity (Ahmed, 2023). According to Fornell and Larcker (1981) it is necessary that $CR \geq 0.7$, $AVE \geq 0.5$, and $CR > AVE$. This condition was also met. This combination of acceptable loadings (> 0.55) and average variance extracted (AVE) and composite reliability (CR) values (all > 0.7) along with acceptable discriminant validity, as measured using the Fornell-Larcker criterion, led us to conclude that our measurement model was convergent valid. In variance-based structural equation modeling (SEM), like PLS-SEM, Heterotrait-Monotrait (HTMT) ratio is recommended (Henseler et al., 2015). This ratio should be $HTMT < 0.85$.

Figure 3: PLS-SEM model

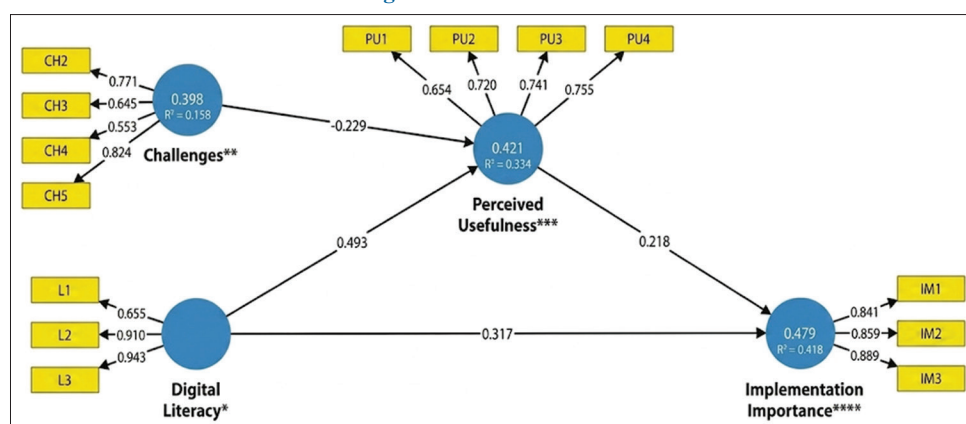


Table 1: Reliability and convergent validity indicators, with descriptive statistics

Constructs and their indicators	Mean	Standard deviation	Factor loadings	Cronbach's alpha	CR	AVE
Implementation importance	3.902	0.061	0.818	0.892	0.891	0.731
IM1	3.871	0.901	0.846			
IM2	3.824	0.862	0.838			
IM3	3.975	0.948	0.883			
Challenges	3.486	0.034	0.701	0.803	0.805	0.512
CH2	3.569	1.042	0.772			
CH3	3.518	1.053	0.602			
CH4	3.561	1.118	0.642			
CH5	3.301	1.072	0.834			
Perceived usefulness	3.871	0.142	0.736	0.834	0.836	0.559
PU1	4.132	0.671	0.671			
PU2	4.021	0.841	0.742			
PU3	3.621	0.981	0.771			
PU4	3.663	0.912	0.803			
Digital literacy	3.604	0.021	0.757	0.858	0.861	0.671
DL1	3.518	0.885	0.652			
DL2	3.538	0.918	0.884			
DL3	3.761	0.913	0.902			

The results indicated that there was no problem with discriminant validity in this study, and that all constructs used in the model are sufficiently different (Table 2). The Challenges construct has acceptable convergent validity with an AVE of 0.512, which is above the recommended threshold of 0.5 by Hair et al. (2017). Although this is somewhat lower than other constructs in this research, it remains acceptable. The HTMT ratios between Challenges and other constructs (0.174 with IM, 0.362 with DL, and 0.401 with PU) are all well below the conservative threshold of 0.85 suggested by Henseler et al. (2015), suggesting good discriminant validity. These findings suggest that the Challenges construct is significantly different from other constructs in the model. Further, the model has good predictive (Q^2 values >0) and explanatory (R^2 values >0.25) power, which also points to the reliability and validity of the model in terms of its use for studying BDA adoption in economic policy.

4.2. Structural Model Assessment

To test for multicollinearity, the VIF values were checked for all the exogenous constructs in the model, which should be <3 according to the literature (Hair et al., 2017). The Value of VIF for the variables DL and PU was 1.318 and 1.074 for the variable Challenges. Therefore, it was concluded that there is no problem with collinearity in this study. Additional criteria of the fit of the structural model were acceptable as well. The coefficient of determination (R^2) which measures the explanatory power of the model was at a satisfactory level, since approximately 42% of the variance of the dependent variable IM can be explained with the independent variables defined in the model (R^2 IM = 0.420). For PU R^2 value was 0.295. It is recommended that the R^2 values be >0.25 (Richter et al., 2016). We also used Stone-Geisser's Q^2 (Geisser, 1974; Stone, 1974) to assess predictive relevance of the model. For this test, PLSpredict function was used with number of folds set to 10. The results showed a satisfactory Q^2 values for two endogenous constructs of the model (Q^2 IM= 0.241, Q^2 PU= 0.236) which according to Hair et al. (2022) should be >0 . For the purpose of hypotheses testing we have used Bootstrap (Bca method; 5000 subsamples; two-tailed t-test; 5% significance level). The results are shown in Table 3. The study showed that there is a positive

Table 2: Discriminant validity indicators

Constructs	IM	Challenges	DL
Challenges	0.174		
DL	0.636	0.362	
PU	0.751	0.401	0.639

Table 3: Testing of the hypotheses

Hypotheses	β coefficients	t- values	P-values	Confirmed
H ₁ : DL→PU	0.469	6.812	0.000	Yes
H ₂ : PU→IM	0.428	4.791	0.000	Yes
H ₃ : DL→IM	0.315	3.742	0.000	Yes
H ₄ : Challenges→PU	-0.219	2.681	0.007	Yes
H ₅ : DL→PU→IM	0.198	3.921	0.000	Yes

and significant link between DL and PU ($\beta = 0.469$; $P < 0.001$) as expected in H₁. Hence, H₁ was supported. H₂ suggested that PU positively affects the level of IM. Our findings suggest that this relationship is positive and statistically significant ($\beta = 0.428$; $P < 0.001$) and hence the H₂ was accepted. H₃ predicted that the level of IM would be positively influenced by DL, which was supported by the results ($\beta = 0.315$; $P < 0.001$) so that the third hypothesis was approved. H₄ assumed that there is negative effect of Challenges on PU (H₄). This was confirmed by the results ($\beta = -0.219$; $P < 0.05$). The H₅ suggested that there is a positive mediated effect of DL on IM via PU (H₅).

The results supported this assumption ($\beta = 0.198$; $P < 0.001$). The PU was found to be a positive mediator of the DL-IM relationship. Given that the direct path between these variables was also significant (H₃), it was shown that the mediation is partial. Although the path coefficients for H₄ ($\beta = -0.219$) and H₅ ($\beta = 0.198$) are lower than H₁-H₃, they reflect important relationships in technology acceptance studies. These effects align with past studies on the adoption of BDA where the effects of implementation challenges are generally moderate on PU (Basit et al., 2025). The size of the mediating effect is consistent with TAM studies where indirect effects tend to show lower effects, but still significant effects (Richter et al., 2016). Based on the

Cohen's f^2 values, it was shown that the effect of Challenges on PU is small ($f^2 = 0.051$), but it is statistically significant ($P < 0.05$) and has practical significance in economic policy development where small decreases in PU can have a significant influence on the implementation process. To determine the effect sizes in the model, Cohen's f^2 was used (Cohen, 1992). It can be seen that the effect of DL on IM is small ($f^2 = 0.119$). The effect of PU on IM is medium in size ($f^2 = 0.228$), as well as the effect of DL on PU ($f^2 = 0.273$). The effect of Challenges on PU was demonstrated to be small, but significant ($f^2 = 0.051$).

4.3. Data Quality and Missing Data Handling

Data quality was checked before the analyses. The survey platform (Nettskjema) was set to not allow for missing values. All 110 responses had complete data on all measurement items. Two responses were initially suspected to be of poor quality due to consistent responses across all items, indicative of satisficing. But these responses contained variability in the demographic items, and were included in the final sample. No responses needed to be imputed, and 110 responses were used for analysis.

5. DISCUSSION

We explored the interplay of DL, PU, implementation challenges and IM of BDA tools in economic governance, as well as the mediation effect of PU. Overall, the results provide a logically consistent and theoretically sound model that is largely in line with technology adoption theories like TAM, HCT and RBV, while also extending their applicability to economic policy development and data-driven policy settings. H_1 showed that DL is a positive predictor of PU. This finding is well supported by TAM that highlights the role of user ability in improving cognitive assessment of system usefulness (Ibrahim and Aduah, 2025). This empirical finding has also been reported by (Jayashree et al., 2026), who report that individual ability enhances performance expectancy of technology. This evidence is further backed by (Ahmed, 2023), who point out that facilitating conditions and individual ability influence performance expectancy. Moreover, Gupta and Jaiswal (2025) contend that usage of innovation is driven by prior knowledge and technical skills. It also adds to recent digital transformation research showing that DL helps interpretation and appreciation of the data system (AbdulKareem and Oladimeji, 2024; Ibrahim and Aduah, 2025). But few studies have indicated that in a highly automated environment, the effect of literacy decreases due to the simplicity of the system (Kalsum et al., 2025), which is slightly different from the strong effect found here. H_2 found PU has a strong influence on IM. This finding is in line with TAM, where PU is the most significant predictor of intention to use (Fattah, 2024). This finding is also supported in (Miraz et al., 2025) who claims that PU is the determinant of intention for continued use of the system. This correlation is also confirmed by Rahimi and Mosalli (2025), who suggest that usefulness directly affects behaviour in their decomposed TPB model. This is also supported by UTAUT, which suggests that the strongest predictor of adoption is performance expectancy (Jain et al., 2024; Gupta and Jaiswal, 2025).

There is no major disagreement in the literature; however, Soomro et al. (2024) also suggests that behavioral intention can be affected

by subjective norms, which this study did not take into account. H_3 found a direct positive impact of DL on IM. This is consistent with HCT that claims that skills directly improve decision-making and productivity (Khabibi and Purnomo, 2026). In the IS field, Ly (2025) also propose direct effects of knowledge on behavioral intention to use. Abd Jalal et al. (2023) also confirm the direct influence of user competence on behavioral intention with facilitating conditions. But Novela et al. (2024) and Hongyun et al. (2025) suggest that such effects are often completely mediated by PU, which is partly contradicted by this study's partial mediation. This implies that in complex policy settings, DL has direct and indirect effects. H_4 indicated that challenges have a negative effect on PU. This finding aligns with previous IS studies that focus on perceived challenges that decrease technology acceptance (Baig et al., 2023). Mondal et al. (2025) and Ullah et al. (2025) also found that organizational resistance and cost concerns negatively impact perceived system value. Likewise, Williams et al. (2024) note that perceived behavioural control constraints impact intention. Rahimi and Mosalli (2025) also confirms that complexity slows down innovation adoption. But the low effect size in this research, compared with previous studies in a resource-constrained environment, where barriers were more influential (Meutia et al., 2025), suggests a moderating effect of economic policy. H_5 was confirmed with a partial mediation effect of PU on DL and IM. This effect is well supported by other TAM research that suggests that PU is a crucial mediator (Rindaşu et al., 2023).

Gupta and Jaiswal (2025) also confirms usefulness as a mediator between system beliefs and intention to use. UTAUT studies also indicate indirect effects via performance expectancy (Venkatesh et al., 2003). But other studies support the full mediation model, especially in mature technology situations (Ly, 2025), which is partly inconsistent with the current finding of partial mediation. This indicates that DL has a direct influence on behaviour, beyond perception. Structurally, R^2 values reflect moderate explanatory capacity, aligns with established SEM criteria (Hair et al., 2017; Richter et al., 2016). Q^2 values indicate predictive importance (Geisser 1974; Stone, 1974). Lack of multicollinearity ($VIF < 3$) enhances model trustworthiness (Cohen, 1992). Effect size measures also confirm PU's dominance (Waqar and Paracha, 2024), and challenges have smaller yet significant impacts (Saeed et al., 2025; Ly, 2025). Validity of measurement is ensured via CR, AVE, Fornell-Larcker, and HTMT criteria, aligns with Fornell and Larcker (1981) and Henseler et al. (2015). These findings guarantee construct validity and reliability, enhancing model reliability. The results are consistent with TAM, UTAUT, HCT and RBV (Mohamad et al., 2025; Gomes, 2025; Khabibi and Purnomo, 2026), confirming the theoretical and contextual relevance of economic policy-driven BDA adoption.

5.1. Theoretical Contributions

This study has significant theoretical implications as it brings together TAM, HCT and RBV to explain BDA adoption in economic policy. From TAM's perspective, the study confirms PU as a critical mediating factor between DL and IM, building on Davis (1989) in a macro-economic policy context. And it reiterates that adoption is not only perception-based but also shaped by the capability and constraint sets. From an HCT standpoint, the

results demonstrate that DL is a key human capital resource, which directly augments cognitive assessment and decision-making. This confirms the human capital reasoning of Becker (skills translate into productivity gains), and its application to digital governance where analytical capability translates into technology prioritisation. The direct and indirect impacts of DL verify its structural and perceptual effects. Viewed through an RBV lens, the research equates DL to an intangible resource, strategically significant to the organisation, that contributes to its analytical advantage. The prominence of PU and moderating effect of challenges confirm that resource value is dependent on institutional fit and environmental constraints. In sum, the TAM-HCT-RBV fusion offers a multi-faceted theoretical perspective on the cognitive, capability and resource aspects of technology adoption.

5.2. Practical Implications

The results provide valuable insights for policy makers, government organizations and economic advisory bodies involved in BDA adoption. First, the significant impact of DL on PU and IM suggests capacity building initiatives. Organizations need to prioritize ongoing training, including skills in advanced analytics, data analysis and digital decision-making processes, to enhance human capital capabilities. Second, the strong effect of PU indicates that governments need to showcase the utility of BDA tools through pilot studies, dashboards and empirical use cases. This will encourage even capable professionals to not fully embrace the tool. Third, the negative effect of challenges suggests that institutional factors (such as cost, privacy and organizational resistance) should be alleviated through supportive governance structures and data policies. Finally, the mediation effect reveals that increasing DL not lead to adoption unless it is accompanied by PU. So, skills development should be complemented with hands-on application. In conclusion, for effective BDA implementation, we need to enhance human skills, system transparency and institutional preparedness for integration in the economic policymaking process.

6. CONCLUSION

This research concludes that the use of DL, PU and challenges influence the perceived usefulness of BDA in economic policy settings. The findings verify that DL is the dominant factor, both directly and indirectly, and PU is an important intermediary variable that translates the capability to implement. While the latter is negatively influential, it plays an important facilitating role in PU. The structural model exhibits significant explanatory and predictive power and confirms the robustness of the TAM model while broadening its scope through the integration of HCT and RBV. The results demonstrate the adoption of technology in economic governance is not merely technological but a complex phenomenon affected by capabilities, perceptions and institutional factors. Significantly, the research reveals that adopting BDA is not just about having the technology but enhancing human skills and perceived value. Although statistically robust, the model's context-specific nature calls for cautious interpretation. However, the study offers a robust foundation for studies on digital transformation in

policy settings and paves the way for more sophisticated theoretical and empirical research in subsequent research.

Our study is not without limitations. First, the cross-sectional study design limits causal inference of relationships, since it reflects perceptions at a single point in time. Longitudinal research offer a greater understanding of the long-term role of digital literacy and perceived usefulness in affecting adoption. Second, while the sample size is adequate to conduct PLS-SEM, it is quite small and narrowly focused and may limit the findings' applicability to the global international economic policy context. Third, the research is based on self-reported data, which could lead to subjective biases and common method bias. Objective performance measures or system use data should be included in future studies to enhance validity. Second, while the proposed model incorporates major constructs, other factors such as organizational culture, top management support and regulation were overlooked. And future studies should also consider cross-country comparisons to understand the role of institutional effects on BDA adoption processes. Further extending the model through mixed methods or qualitative findings may help understanding of behavioural factors. Finally, future research might explore moderating variables such as age, experience or firm size to increase theoretical accuracy and predictive ability.

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APPENDIX

Appendix A: Questionnaire Items

This appendix presents the final measurement items used to collect data for the study. All items were measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

A1. Digital Literacy

- DL1: I am confident in using digital tools for data analysis in my professional tasks.
- DL2: I have sufficient skills to work with software used for economic data processing.
- DL3: I can easily interpret and analyze data using digital platforms and applications.

A2. Perceived Usefulness

- PU1: Using Big Data Analytics improves the quality of my policy-related decisions.
- PU2: BDA tools enhance my efficiency in analyzing economic data.
- PU3: BDA tools help me make faster and more accurate policy decisions.
- PU4: Overall, I find BDA tools useful in economic policy formulation.

A3. Implementation Importance

- II1: Implementing Big Data Analytics is important for modern economic policy-making.
- II2: Adoption of BDA tools should be a priority in my organization.
- II3: Economic institutions should invest more in Big Data Analytics systems.

A4. Challenges

- CH2: Lack of technical infrastructure is a barrier to using BDA tools.
- CH3: Limited training opportunities hinder effective use of BDA tools.
- CH4: Resistance to organizational change affects the adoption of BDA tools.
- CH5: Data privacy and security concerns limit the use of BDA tools.