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TESIS DOCTORAL

ESSAYS ON SOCIAL MEDIA AND FIRM COMPETITIVENESS

MENCIÓN DE DOCTORADO INTERNACIONAL

Tesis doctoral presentada por:

Ana Castillo López

Dirigida por:

Prof. Dr. Francisco Javier Lloréns Montes
Prof. Dr. José Benítez Amado

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A mis seres queridos,
por ser y estar.

A mi madre,
por ser el motor y el eje
de mi vida.

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SR. COORDINADOR DEL PROGRAMA DE DOCTORADO EN CIENCIAS ECONÓMICAS Y EMPRESARIALES

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INTRODUCCIÓN

1. INTRODUCCIÓN

Introducción

Durante la última década, los medios sociales como blogs, plataformas para compartir fotos, juegos sociales, microblogs, aplicaciones de chat y redes sociales han experimentado una rápida proliferación. Tal es esta proliferación, que de los 7,476 billones de personas que forman el total de la población, 3,773 billones son usuarios de internet, siendo 2,789 billones los usuarios activos en medios sociales, lo que supone alrededor de un 37% de la población de la Tierra (IDC Spain, 2019; Kemp, 2017). Se espera que el uso de medios sociales alcance la cantidad de 2,95 billones de usuarios para 2020 (Statista, 2018). Esta popularidad entre los consumidores ha hecho que las empresas busquen trasformar sus negocios usando los medios sociales y capitalizar su valor financiero (Luo et al., 2013). Las empresas normalmente empiezan usando los medios sociales como herramienta de marketing para comunicarse con sus consumidores, sin embargo, cada vez más están siendo usadas para colaboración interna, gestionar el talento y las operaciones (Kane 2015), y para construir capital humano, social, organizacional, económico y simbólico (Mandviwalla y Watson, 2014). Los medios sociales tales como Facebook y Twitter crean nuevas oportunidades para las empresas, mejorando las operaciones internas de las mismas y permitiendo nuevas formas de colaboración con todos sus *stakeholders* (Culnan et al., 2010), convirtiendo a los medios sociales es una fuente potencial de generación de valor para la empresa (Aral et al., 2013; Leonardi, 2014). Además, los medios sociales han supuesto un profundo cambio en el boca a boca, pasando de que el público objetivo sea uno o pocos amigos, a que el público objetivo sea el mundo entero (Duan et al., 2008). Este boca a boca en medios sociales es un canal dominante para aumentar el conocimiento del cliente, y por el que los usuarios comunican sus opiniones y creencias (Oh et al., 2017), y crean contenido. Por tanto, el uso por parte de las empresas de los medios sociales más allá del marketing es un nuevo fenómeno empresarial de vital importancia y gran potencial que necesita ser entendido.

Hoy día, vivimos en un tiempo de cambio sin precedentes. Solo en los dos últimos años, se han creado el 90% de todos los datos del mundo (IDC Spain, 2019). Por ello, en este contexto de entorno turbulento, la innovación es un factor clave para el éxito competitivo de la empresa (Kleis et al., 2012). Las empresas necesitan recoger, monitorizar y analizar datos para poder conseguir mayor valor de negocio (He et al., 2015) en forma de innovación. Los medios sociales pueden proveer datos sobre consumidores y competidores para convertirlos en información y conocimiento y, por tanto, pueden considerarse como facilitadores estratégicos de conocimiento que pueden ayudar a las empresas a innovar más y mejor (Aral et al., 2013; Leonardi, 2014). Las empresas pueden llevar a cabo campañas en redes sociales para generar conocimiento sobre productos e iniciativas que se realicen, y para testar opiniones, impresiones e ideas de los consumidores (Dong y Wu, 2015). A través de estas iniciativas se genera un poderoso boca a boca y un *engagement* del consumidor que puede afectar a los resultados empresariales. Por ejemplo, la empresa de patatas fritas Lay's promovió una campaña en redes sociales llamada "*Do us a flavor*". Esta campaña tenía como objetivo innovar sobre el nuevo sabor de patatas fritas considerando las ideas que provenían de sus consumidores. El resultado fue la selección de un nuevo sabor, el cual fue el más votado por los usuarios *Southern Biscuits and Gravy.*

Sin embargo, generar y recolectar datos de los medios sociales no es suficiente para hacer un uso eficiente de la información que le permita innovar y conseguir mejores resultados empresariales. Los medios sociales deben estar racionalmente integrados en la infraestructura de tecnologías de la información (TI) para poder servir como un complemento a las actividades de gestión de conocimiento. Además, es necesario que se monitorice, se analice e identifique la información de medios sociales que es relevante y crítica para ser transformada en información y conocimiento (talento analítico de negocio), y en última instancia en ganancias de negocio (Ransbotham et al., 2015), teniendo en consideración el boca a boca generado y el *engagement* del consumidor. Por ello, es importante conocer el papel que tiene en la creación de valor la capacidad de medios sociales (capacidad de la empresa para usar los medios sociales para actividad corporativas) en conjunto con otros recursos y capacidades como la gestión del conocimiento o el talento analítico de negocio (talento de las empresas para aplicar analítica de negocios de forma efectiva a través de la transformación de datos en conocimiento valioso para el apoyo de las actividades organizativas), y cómo es una pieza clave para la generación de *engagement* del consumidor.

El uso de medios sociales para actividades de negocio está alcanzando un gran desarrollo en empresas. Estudios previos en el campo de investigación de Sistemas de Información han contribuido de forma significativa en dar respuesta a la pregunta de cómo los medios sociales contribuyen a la creación de valor (ej., Braojos, 2018), sin embargo, nuestro conocimiento sobre este nuevo fenómeno corporativo está en sus etapas iniciales. Debido a la novedad de dicho fenómeno y a la creciente presencia e importancia del mismo en los negocios, la incorporación de los medios sociales en la investigación en Sistemas de Información es (casi) una necesidad hoy día.

El presente estudio tiene como objetivo principal el análisis de cómo la capacidad de medios sociales permite a las empresas generar valor y mejorar sus resultados corporativos.

1.1. Marco general de la tesis doctoral

El marco general en el que se enmarca dicho trabajo es en el área de investigación de Sistemas de Información. Dentro de esta área, el trabajo se contextualiza en la importancia de la TI en la creación de valor de negocio y en la generación de resultados corporativos. Específicamente, dicha tesis se centra en el papel de los medios sociales en esta creación de valor. Numerosos estudios previos, basándose en la perspectiva de las capacidades organizativas facilitadas por la TI, argumentan que la TI permite a las empresas generar valor empresarial a través de capacidades organizativas intermedias, como flexibilidad, integración de la cadena de suministro, gestión del talento, aprendizaje organizativo y gestión del conocimiento (ej., Ajamieh et al., 2016; Benitez et al., 2015; Benitez et al., 2018a). Por tanto, la literatura previa sobre la generación de valor facilitada por la TI, apoya y defiende la relación existente entre los recursos de TI y el desempeño organizativo a través de variables intermedias (Devaraj et al., 2017).

Los medios sociales son un recurso específico de TI definido como tecnologías digitales que dan soporte a la transferencia de información entre los distintos usuarios (Braojos, 2018). A pesar de la contribución realizada por estudios previos en explicar cómo los medios sociales crean valor (ej., Braojos, 2018), el desarrollo de la literatura sobre la generación de valor facilitada por la capacidad de medios sociales se encuentra en un estadio inicial. Por ello, existen confrontaciones entre la comunidad científica. La mayoría de estudios previos coinciden en señalar el efecto positivo de los medios sociales en la generación de valor en las empresas. Por ejemplo, Wagner y Wagner (2013) señalan que el uso de comunidades online ayuda a las empresas a desarrollar capacidades dinámicas para crear valor de negocio. Yu et al., (2013) sugieren que el uso de los medios sociales tiene un efecto más fuerte en los resultados de las empresas que los medios tradicionales. Leonardi (2014) apunta que la visibilidad de la comunicación facilitada por los medios sociales mejora los resultados de innovación de las empresas. Sin embargo, este efecto positivo de los medios sociales en la generación de valor en las empresas se podría contraargumentar, sugiriendo que los empleados de las empresas pueden pasar un tiempo improductivo usando los medios sociales, mientras que de otro modo, podrían invertir dicho tiempo en la ejecución de otras actividades encaminadas a mejorar los resultados empresariales, como por ejemplo, llevando a cabo actividades de innovación, a este fenómeno se le conoce como *cyberloafing* (Glassman et al., 2015). Por este motivo, es necesario una mayor profundización en el desarrollo y análisis empírico del conocimiento sobre cómo los medios sociales ayudan a las empresas a crear valor de negocio. Esta tesis doctoral analiza cómo la capacidad de medios sociales, a través de una serie de mecanismos y recursos/capacidades intermedios y/o complementarios, ayuda a la consecución de un mayor desempeño organizativo.

1.2. Delimitación del tema objeto de estudio

La creación de valor de negocio en las empresas por parte de los medios sociales es un fenómeno corporativo cuyo conocimiento está en sus primeras etapas. Algunos autores han analizado el papel que juegan los medios sociales para las actividades de negocio. Por ejemplo, Wagner & Wagner (2013) encuentran que el uso de comunidades online ayuda a las empresas a desarrollar capacidades dinámicas para crear valor de negocio. Por su parte, Leonardi (2014) pone de manifiesto que los medios sociales de la empresa mejoran la visibilidad de la comunicación para mejorar el meta-conocimiento, impulsando mejorar la innovación. A pesar de los significativos progresos en dar respuesta a la pregunta de cómo los medios sociales contribuyen en la creación de valor de negocio, un gran camino quedar por recorrer para conseguir entender los mecanismos que intervienen en dicha relación.

La capacidad de medios sociales hace referencia a la capacidad de la empresa en usar los medios sociales para actividades corporativas con fines de negocio. En definitiva, es la habilidad que tiene la empresa para usar medios sociales como Facebook, Twitter o blog para sus actividades empresariales. Algunas de las mayores aportaciones al conocimiento de la capacidad de medios sociales han sido las realizadas por Braojos (2018). Por un lado, Braojos (2018) sugiere que el desarrollo tanto por separado como conjunto de la capacidad de medios sociales y la capacidad de comercio electrónico influye en el aumento de la participación del cliente mejorando el desempeño organizativo del mismo. Mientras que por otro lado pone de manifiesto cómo la capacidad de medios sociales tiene un efecto positivo en el desempeño innovador de la empresa a través del desarrollo conjunto de una serie de capacidades (ej., orientación al mercado, coordinación, capacidad de absorción, mente colectiva, y flexibilidad de negocio).

Además de todo esto, los medios sociales han supuesto una revolución en el boca a boca y en el *engagement* del consumidor, aumentando de forma exponencial el público objetivo al que se dirige (Duan et al., 2008) y, por tanto, aumentando también de forma exponencial la importancia de entender dicho hecho. Especialmente importante es comprender dicho fenómeno en la industria del entretenimiento como, por ejemplo, la industria cinematográfica, ya que las películas, al ser consideradas como un artefacto cultural, tienden a atraer un gran interés por parte de los usuarios y la comunicación sobre las películas en medios sociales se espera que sea muy alta. Por tanto, esta creciente importancia del *engagement* del consumidor a través de los medios sociales es un aliciente para estudiar su papel, sus principales beneficios y retos, y el papel que van a tener los directivos en usar dicha información para pronosticar las ventas y desarrollar estrategias efectivas para incrementar el resultado organizativo.

En la actualidad, la creación de valor de negocio de las empresas por parte de los medios sociales sigue suscitando un creciente interés tanto en lo académico como en lo práctico. Esto es debido a la rápida proliferación que está experimentando y a la magnitud de la misma, donde un 37% de la población de la Tierra son usuarios activos en medios sociales, cifra que se espera siga aumentando en los próximos años (IDC Spain, 2019; Statista, 2018). Así, y tal y como han reconocido en el ámbito académico (ej., Braojos, 218), los medios sociales se consideran como una herramienta esencial de vital importancia para la creación de valor de negocio en las empresas.

1.3. Objetivos de la investigación

La delimitación del tema objeto de estudio permite identificar el objetivo principal que el presente trabajo pretende conseguir. El principal objetivo de esta tesis doctoral es el de analizar cómo la capacidad de medios sociales permite a las empresas generar valor y mejorar sus resultados corporativos. Para ello, se identifican una serie de capacidades intermedias y complementarias que se relacionan con dicha capacidad, y se analiza su vinculación con las mismas.

En término general, este trabajo de investigación pretende dar respuesta fundamentalmente a los siguientes interrogantes:

- ¿La capacidad de medios sociales ayuda a las empresas a generar valor y mejorar sus resultados organizativos?
- ¿Qué mecanismos y capacidades intermedias y complementarias son necesarias para que la capacidad de medios sociales repercuta de forma positiva en la generación de valor y mejora de los resultados corporativos?

Al dar respuesta a estas preguntas de investigación lograremos profundizar en el conocimiento sobre el efecto que tiene la capacidad de medios sociales sobre los resultados empresariales considerando otros mecanismos y capacidades intermedias y complementarias necesarios.

Así, una vez acotado el objeto de estudio principal del presente trabajo, se formulan los objetivos específicos que se dividen en tres:

En el segundo capítulo, el objetivo es estudiar el papel moderador que ejerce la capacidad de medios sociales sobre el impacto de la TI en el resultado de innovación empresarial tomando en consideración otras variables organizativas que median dicha relación.

En el tercer capítulo, el objetivo es estudiar el impacto de la capacidad de medios sociales en el resultado de innovación empresarial tomando en consideración otras variables organizativas que median y moderan dicha(s) relación(es).

En el cuarto capítulo, el fin último es analizar si el *engagement* del consumidor a través de los medios sociales, impacta sobre los resultados empresariales en la industria cinematográfica.

1.3.1. Impacto de la TI en el desempeño innovador: Papel moderador de la capacidad de medios sociales

Estudios anteriores se han centrado principalmente en estudiar el efecto que tiene la TI en las actividades de gestión del conocimiento y en los resultados (Choi et al., 2010; Real et al., 2006; Tanriverdi, 2005). Además, se han enfocado en examinar la relación existente entre la TI y las actividades y los resultados de innovación (Chen et al., 2015; Kleis et al., 2012; Kumar y Bose, 2016); y, por otro lado, la relación entre la gestión del conocimiento y la innovación. Sin embargo, salvo muy pocas excepciones (Eseryel, 2014; Joshi et al., 2010), el análisis del impacto de la TI sobre la gestión del conocimiento y éste sobre el desempeño innovador en un mismo estudio es muy limitado. Por ello, en el segundo capítulo de este trabajo, una de las preguntas de investigación a las que se quiere dar respuesta es si la infraestructura de TI impacta en el desempeño innovador de las empresas a través de la ambidestreza de conocimiento (i.e., la habilidad de las empresas para usar una combinación equilibrada de exploración y explotación de conocimiento con propósitos operativos).

El uso de los medios sociales para actividades de negocio más allá del marketing está en su estadio inicial (Aral et al., 2013; Braojos et al., 2015). Algunos son ya los autores que se hacen eco de la importancia que tiene los medios sociales como facilitador de la gestión del conocimiento y, en algunos casos, como fuente de innovación (Bengtsson y Ryzhkova, 2013). Sin embargo, el papel que juega la capacidad de medios sociales en la relación existente entre la infraestructura de TI, la ambidestreza de conocimiento y el desempeño innovador no ha recibido suficiente atención en el área de investigación de Sistemas de Información. Este segundo capítulo del trabajo de investigación, por tanto, pretende dar respuesta a otra de las preguntas de investigación planteadas, que es si las relaciones previamente establecidas (la relación existente entre la infraestructura de TI, la ambidestreza de conocimiento y el desempeño innovador) se pueden ver amplificadas en empresas que tengan un mayor desarrollo de la capacidad de medios sociales. Dicho de otro modo, la pregunta a la que se quiere responder es si la capacidad de medios sociales juega un papel moderador (i.e., potenciador) en estas relaciones.

Por tanto, el segundo capítulo de este trabajo de investigación tiene como principal pretensión analizar si y cómo la infraestructura de TI permite el desarrollo de la ambidestreza de conocimiento en las empresas, y cómo este a su vez puede incrementar el desempeño innovador de las mismas, y analizar el papel amplificador y potenciador que tiene la capacidad de medios sociales en estas relaciones.

1.3.2. Impacto de la capacidad de medios sociales en el desempeño innovador: Papel moderador del talento analítico de negocio

Una vez visto el papel moderador de la capacidad de medios sociales en la relación existente entre la ambidestreza de conocimiento y el desempeño innovador, es interesante profundizar en el papel que puede jugar como facilitadora de dicha relación. Estudios previos se han centrado principalmente en el efecto de la TI en la gestión de conocimiento y en el desempeño organizativo (Choi et al., 2010; Real et al., 2006; Tanriverdi, 2005) sin analizar el impacto de la capacidad de medios sociales (recurso específico de TI) en la misma. Por tanto, y a pesar de que algunos autores señalen la importancia de los medios sociales como proveedores de una gran cantidad de información sensible para la innovación (Aral et al., 2013), nuestro conocimiento sobre el impacto de la capacidad de medios sociales en la ambidestreza de conocimiento y éste en el desempeño innovador de la empresa es muy acotado. Uno de los objetivos específicos de este tercer capítulo es el de analizar el impacto que tiene la capacidad de medios sociales en la ambidestreza de conocimiento, y éste a su vez en el desempeño innovador de la empresa.

El talento analítico de negocio hace referencia al talento de las empresas para aplicar la analítica de negocios de forma efectiva mediante la transformación de datos en conocimiento valioso para apoyar las actividades organizativas (Ransbotham et al., 2015). Dicho talento analítico de negocio es un recurso de TI valioso y escaso entre las empresas ya que, a pesar del potencial que tiene como creador de valor de negocio, hay escasez de directivos y gerentes talentosos en analítica de negocios según McKinsey Global Institute

(Ransbotham et al., 2015). Por ello, una gran cantidad de puestos de trabajo han demandado experiencia en analítica de negocio. Como consecuencia, otro de los objetivos específicos que se pretenden alcanzar con el tercer capítulo de este trabajo de investigación es analizar si aquellas empresas que poseen un mayor talento analítico pueden amplificar y fortalecer las relaciones existentes entre la capacidad de medios sociales, la ambidestreza de conocimiento, y el desempeño innovador de las empresas.

En general, el tercer capítulo de este trabajo de investigación se encarga de dar respuesta a las siguientes preguntas: 1) ¿Impacta (y cómo) la capacidad de medios sociales en el desempeño innovador de la empresa a través de la ambidestreza de conocimiento? y 2) ¿pueden estas relaciones verse fortalecidas cuando la empresa posee talento analítico de negocio?

1.3.3. Impacto del engagement del consumidor a través de los medios sociales en el desempeño empresarial en la industria del cine: Engagement personal y engagement interactivo

El análisis de la importancia del *engagement* del consumidor a través de los medios sociales ha despertado un creciente interés (Giamanco y Gregoire, 2012). Este fenómeno es especialmente importante en el contexto de entretenimiento como es la industria cinematográfica ya que las películas tienden a atraer un gran interés por el público, y esta comunicación entre usuarios sobre películas se espera que sea alta (Liu, 2006) en medios sociales. La creciente importancia del *engagement* del consumidor a través de medios sociales ha alentado a los académicos a empezar a estudiar su papel, sus beneficios, sus principales retos y el rol que juegan los directivos para ser capaces de desarrollar estrategias efectivas para aumentar los resultados. Sin embargo, pocos son los estudios todavía que representan esta emergente área de investigación en Sistemas de Información; por ello, el conocimiento del impacto del *engagement* del consumidor a través de los medios sociales en la predicción de futuras ventas en la industria cinematográfica es muy limitado. Como consecuencia, el objetivo específico que se pretende conseguir con el cuarto capítulo de este trabajo de investigación es examinar el papel que desempeña el *engagement* del consumidor a través de los medios sociales en la predicción de los resultados empresariales en la industria cinematográfica.

De forma específica, el cuarto capítulo, por tanto, se encarga de dar respuesta a las siguientes preguntas de investigación: 1) ¿Puede el *engagement* del consumidor a través de los medios sociales predecir e influir los resultados empresariales futuros en la industria cinematográfica (i.e., el desempeño de las películas)? y 2) ¿cómo el *engagement* personal y el *engagement* interactivo interaccionan para afectar de forma positiva al desempeño de las películas?

1.4. Estructura del trabajo de investigación

El presente trabajo de investigación está formado por un total de tres grandes bloques que se detallan en cinco capítulos. El primer bloque abarca la introducción de dicho trabajo y está formado por un solo capítulo (Capítulo 1). En el segundo bloque se encuentra el cuerpo central de esta tesis doctoral en el que se enmarcan los tres trabajos de investigación específicos que la forman, este bloque está compuesto por un capítulo por cada trabajo de investigación específico (Capítulo 2, 3 y 4). El tercer bloque corresponde con la conclusión de dicho trabajo de investigación y está compuesto por un capítulo (Capítulo 5).

En el Capítulo 1 se introduce el tema objeto de estudio de dicho trabajo de investigación, es decir, el papel que desempeña la capacidad de medios sociales como generador de valor de negocio en las empresas. Para ello, se comienza mostrando la importancia de los medios sociales para las empresas en la actualidad, y cómo este reciente fenómeno ha sido abordado previamente en la literatura de Sistemas de Información. Se enmarca de forma general dicho trabajo de investigación, y se delimita el tema objeto de estudio. Este capítulo, además, establece de forma general y específica los objetivos perseguidos con dicho trabajo, y justifica su interés tanto en lo académico como en la práctica empresarial.

En el Capítulo 2 se examina, en primer lugar, el impacto de la TI en la ambidestreza de conocimiento de la empresa, y el impacto de esta ambidestreza en el desempeño innovador de la misma y, en segundo lugar, el papel amplificador que juega la capacidad de medios sociales en estas relaciones. Esta teoría propuesta ha sido testada usando datos secundarios de una muestra de 100 pequeñas empresas estadounidenses.

En el Capítulo 3 se explora el efecto de la capacidad de medios sociales en el desempeño innovador de la empresa a través de la ambidestreza de conocimiento, y cómo el talento analítico de negocio amplifica dichas relaciones. Por tanto, la ambidestreza de conocimiento de la empresa se considera un mecanismo intermedio por el cual la capacidad de medios sociales mejora el desempeño innovador de la misma. Por su parte, el talento analítico de negocio se considera un mecanismo moderador en esta ecuación. Al igual que en el trabajo de investigación específico desarrollado en el Capítulo 2, testamos este modelo en una muestra de 100 pequeñas empresas estadounidenses, usando datos secundarios.

En el Capítulo 4 se analiza el papel que juega el *engagement* del consumidor a través de los medios sociales en la predicción e influencia en el desempeño empresarial futuro en la industria cinematográfica. Por tanto, este capítulo examina el impacto que tiene el *engagement* del consumidor, específicamente el *engagement* personal y el *engagement* interactivo, en el desempeño de las películas, así como el impacto de la interacción de ambos tipos de *engagement* en este desempeño. En dicho trabajo, testamos el modelo en una muestra de 966 películas estrenadas en Reino Unido y España.

Por último, en el Capítulo 5 se concluye el trabajo de investigación mostrando las contribuciones que aporta el mismo a la literatura de Sistemas de Información. Para ello, se detallan una serie de implicaciones teóricas y empíricas para el ámbito académico, y para la práctica empresarial. Se reconoce también una serie de limitaciones a tener en cuenta como áreas de mejora para futuras líneas de investigación, y se termina reflexionando con unas consideraciones finales.

1.5. Justificación e interés de la investigación

Hoy día estamos viviendo en un tiempo de cambio sin precedentes, donde el 90% de los datos existentes a nivel mundial han sido generados tan solo en los últimos dos años (IDC Spain, 2019). Por lo tanto, es importante tener herramientas como los medios sociales que permitan acceder y hacer un uso efectivo de la información para conseguir mejorar el desempeño organizativo. Además, en este contexto caracterizado por la turbulencia, la innovación es un factor clave para el éxito competitivo de la empresa (Kleis et al., 2012), por lo que es importante conocer el papel que juega los medios sociales en el desempeño de innovación empresarial. Sin embargo, la creación de valor de negocio por parte de los medios sociales no se entiende de forma aislada, sino que hay que considerar otros mecanismos y capacidades intermedias y complementarias necesarias para comprender dicho fenómeno.

A pesar de progresos significativos en responder a la pregunta de cómo los medios sociales contribuyen a la creación de valor (ej., Braojos, 2018), el conocimiento que existe sobre este fenómeno corporativo es limitado y está en sus etapas iniciales. Esta tesis doctoral explica de forma teórica y demuestra de forma empírica cómo los medios sociales ayudan a las empresas a generar valor de negocio.

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IT-ENABLED KNOWLEDGE AMBIDEXTERITY AND INNOVATION PERFORMANCE IN SMALL U.S. FIRMS: THE MODERATOR ROLE OF SOCIAL MEDIA CAPABILITY

2

2. IT-ENABLED KNOWLEDGE AMBIDEXTERITY AND INNOVATION PERFORMANCE IN SMALL U.S. FIRMS: THE MODERATOR ROLE OF SOCIAL MEDIA CAPABILITY

Abstract

This study examines the impact of information technology (IT)-enabled knowledge ambidexterity on innovation performance, and the potential moderator role of social media capability on a sample composed of 100 small U.S. firms. The empirical analysis suggests that IT infrastructure enables the firm to explore new knowledge and exploit existing/new knowledge to innovate more and better. We also find that social media capability has a positive moderator role in this equation: IT infrastructure and social media capabilities work together to enable knowledge ambidexterity.

Keywords: IT infrastructure, knowledge exploration and exploitation, social media capability, innovation performance.

2.1. Introduction

In the contemporary business environment, the firm's capture, analysis, and dissemination of knowledge are knowledge management activities that have the potential to explain a significant portion of variation in firm performance (Alavi & Leidner, 2001; Sher & Lee, 2004). For instance, Capgemini (a European consulting firm) and Ernst & Young (a North American consulting firm) have perceived their knowledge management activities as strategic for past merger success. They consider gathering, selecting, filtering, analyzing, and disseminating internal and external knowledge as critical to their business models (e.g., satisfying their customer's needs and improving sales) (Lara et al., 2010).

Information technology (IT) enables social interaction among the organization's members to share knowledge and apply it effectively in the firm's business activities (Mueller et al., 2011). IT support is thus a key facilitator of a firm's knowledge management (Pinjani & Palvia, 2013). Siemens, for example, creates advantage from a sustainable knowledge network (Technoweb) created to solve daily operational problems. Siemens uses IT to manage internal collaboration and share knowledge among experts, facilitate real-time communication exchange, and find hidden knowledge to save work time and solve problems faster and more efficiently (Grau et al., 2004; Lakhani et al., 2015).

Using social media for business activities (i.e., beyond marketing) is a new corporate phenomenon, and our understanding of the Information Systems (IS) field is in the initial stages (Aral et al., 2013; Braojos et al., 2015a; Leidner et al., 2010). Incorporation of social media is thus almost a necessity in today's IS research. Social media may provide additional customer and industry data to digitally convert information into knowledge to innovate. Such incorporation may suggest a potential complementary role of social media in the relationships between IT, knowledge management, and innovation outcomes—the central thesis of this investigation. A counter-argument may be that the firm's employees may spend unproductive time on social media that could otherwise be used for knowledge exploitation and innovation, a phenomenon referred to as cyber-loafing (e.g., Glassman et al., 2015). If the firm manages social media appropriately, however, they can become a golden source of data. If they are integrated rationally into the firm's IT infrastructure, they can provide an excellent complement to knowledge exploration and exploitation to achieve more and better innovations. This theoretical argument needs more in-depth development and empirical testing, and our investigation aims to connect all pieces properly to complete the puzzle.

This research attempts to answer two key research questions: 1) Does IT infrastructure impact innovation performance through knowledge ambidexterity (i.e., the firm's ability to use a well-balanced combination of knowledge exploration and exploitation for operational purposes)? and 2) Can these relationships be strengthened in firms that have developed social media capability (i.e., the firm's ability to leverage social media to execute business activities)? This investigation thus examines both the impact of IT-enabled knowledge ambidexterity on innovation performance and the potential moderator role of social media capability. This research theorizes that IT infrastructure enables development of knowledge ambidexterity to increase innovation performance, and that social media capability may perform a moderator role in this equation. We test our theory using partial least squares (PLS) path modeling with a secondary dataset on a sample of 100 small U.S. firms.

This work makes several contributions to the field of IS. First, it provides new evidence to develop a different explanation of how IT infrastructure enables management of organizational knowledge to increase innovation performance than the explanation given in prior IS research, and develops this argument by focusing on knowledge ambidexterity in small firms. Second, the investigation develops the concept of social media capability for business activities and theorizes how this capability moderates the relationship between IT infrastructure and knowledge ambidexterity.

The remainder of the paper is organized as follows. Next, we discuss the literature review that informs this work. The third section explains the theories on which the proposed model is based and develops the hypotheses. The fourth and fifth sections present the research methodology (sample, data, and measures), empirical analysis, and results. Subsequently, the manuscript concludes with a discussion of the findings and implications of the research.

2.2. Literature review

2.2.1. IT, knowledge management, and innovation performance

Prior IS research has focused primarily on the effects of IT on knowledge management activities and performance (e.g., Choi et al., 2010; Real et al., 2006; Tanriverdi, 2005). Sabherwal and Sabherwal (2005) examine the effects of IT-based knowledge management announcements on short-term firm value. Tanriverdi (2005) focuses on large U.S. firms to examine how IT relatedness impacts financial performance through knowledge management capability. Choi et al., (2010) and Kettinger et al., (2015) explore the role of IT support in knowledge-sharing behavior and the possible impact of both on team performance.

Another major area of IS literature studies the relationship between IT and innovation activities, and performance (e.g., Chen et al., 2015; Kleis et al., 2012; Kumar & Bose, 2016), as well as the relationship between knowledge management and innovation (e.g., Leal et al., 2014). For example, Kleis et al., (2012) posit that IT and research and development activities positively affect innovation production.

With a few exceptions (e.g., Eseryel, 2014; Joshi et al., 2010), however, analysis of the impact of IT on knowledge management and innovation activities *in the same study* is very limited. On examining the effect of IT-enabled knowledge capabilities (potential and realized absorptive capacity) on firm innovation, Joshi et al., (2010) find that IT applications enable the firm to absorb knowledge to increase innovation outputs. Eseryel's (2014) case study illustrates that IT supports the firm's processes of knowledge creation (i.e., socialization, externalization, combination, and internalization) for open innovation activities. Our research differs in focusing on knowledge ambidexterity in small firms and tests empirically how IT infrastructure enables the exploration and exploitation of organizational knowledge to improve innovation performance. Knowledge ambidexterity refers to the firm's ability to use a well-balanced combination of exploration and exploitation of organizational knowledge for operational purposes (Durcikova et al., 2011). Table 2.1 presents our comprehensive analysis of prior research on IT, knowledge management, and firm performance.

2.2.2. Social media, knowledge management, and innovation performance

The prior literature views social media technologies as supportive of the firm's knowledge management due to their presence and interactivity in assisting firms' knowledge management efforts (e.g., Mueller et al., 2011; Pan et al., 2015; Sultan, 2013). For example, Mount and Garcia (2014) propose a four-step framework for social media use in business activities: scan, engage, learn, and internalize.

Table 2.1: Comprehensive analysis of prior research on IT, knowledge management, and firm performance

Authors	Source	Key finding(s)
Sabherwal and Sabherwal (2005)	Decision Sciences	Cumulative abnormal returns resulting from IT-based knowledge management announcements are greater when knowledge management is aligned with the firm's efficiency, and when the firm has greater stability, greater diversification, smaller size, and lower profitability
Tanriverdi (2005)	MIS Quarterly	IT relatedness has a positive effect on knowledge management capability, which in turn has a positive effect on the firm's financial performance
Choi et al., (2010)	MIS Quarterly	IT support has a positive impact on the development of transactive memory systems in teams. IT support and transactive memory systems have a positive impact on knowledge sharing and knowledge applications, which in turn impact team performance
Joshi et al., (2010)	Information Systems Research	IT provides a set of knowledge capabilities that contribute to firm innovation in different ways. IT applications enable development of a potential absorptive capacity that in turn facilitates realized absorptive capacity, and the latter improves development of new ideas (patents)
Kettinger et al., (2015)	European Journal of Information Systems	When people perceive strong IT support, they are likely to be confident in their information management skills and subsequently more likely to cue into a psychological climate that motivates knowledge sharing, which in turn promotes knowledge sharing

The new knowledge management era is becoming increasingly aware of online social media and cloud computing as enablers of knowledge, in some cases even as strategic sources of innovation (e.g., Bengtsson & Ryzhkova, 2013; Leonardi, 2014). Leonardi (2014), for example, provides a theory of communication visibility and asserts that firms can enhance meta-knowledge and foster improvements in innovativeness by implementing social media. Such use of social media for business activities (i.e., beyond marketing) is a new corporate phenomenon, and our understanding of it is in the initial stages (Aral et al., 2013; Braojos et al., 2015a). This topic has not received adequate attention in the IS research. Our paper analyzes the moderator role of social media in knowledge ambidexterity and innovation performance. Table 2.2 presents our comprehensive analysis of prior research on social media and business activities, which continues Braojos et al.,'s (2015a) literature review.

Table 2.2: Comprehensive analysis of prior research on social media for business activities

Authors	Source	Key finding(s)
Beck et al., (2014)	MIS Quarterly	The firm's social media establish electronic networks of practices and foster knowledge exchange among employees. The individual characteristics of knowledge seekers and knowledge contributors impact quality of knowledge exchanged
Leonardi (2014)	Information Systems Research	The firm's social media enhance communication visibility to improve meta-knowledge, fostering improvements in innovativeness
Mandviwalla and Watson (2014)	MIS Quarterly Executive	To generate capital from social media strategy, one must establish capital goals (what capital one wants to generate), and apply four complementary tactics to achieve the goals: (1) listening and branding, (2) mining and deciding, (3) conversing and sharing, and (4) co-creating and innovating
Mount and Garcia (2014)	MIT Sloan Management Review	Social media can enable the firm to conduct market research on a larger scale and facilitate brand rejuvenation. Converting the mass of user-generated content into knowledge requires a framework. This paper provides a four-step framework for social media use in business activities: scan, engage, learn, and internalize
Kane (2015)	MIS Quarterly Executive	The two fundamental social media capabilities are establishing social media and accessing digital content. These two capabilities influence employee performance and user behavior
Pan et al., (2015)	Information & Management	Social media support intensifies knowledge exchange among friends in a virtual community of practice

2.2.3. *Knowledge management, organizational ambidexterity, and knowledge ambidexterity*

Organizational ambidexterity refers to the firm's ability to manage tensions between exploratory and exploitative organizational behaviors (Benner & Tushman, 2003; March, 1991). Different literature streams, including organizational learning, technology and innovation management, strategy, and organizational theory, have contributed to the research on organizational ambidexterity. Building on the technology and innovation management literature, we can consider ambidextrous firms as organizations that excel at exploiting existing products (i.e., repetitive and incremental innovation)[1] and exploring new products (i.e., radical innovation)[2] (Tushman & O'Reilly, 1996). Drawing on the organizational learning literature, March (1991) proposes that exploitation and exploration are two different learning activities. Whereas exploitation involves the set of practices implemented to make the most of new/existing knowledge, exploration indicates the set of practices that search and experiment with new knowledge. We draw on this body of literature to extrapolate organizational ambidexterity to the context of exploration and exploitation of organizational knowledge, generating the concept of knowledge ambidexterity.

Knowledge management is the continuous process of acquisition, creation, sharing, storage (Mueller et al., 2011), and use of knowledge at firm level (e.g., Choi et al., 2010). The process starts with obtaining new knowledge.

[1] Repetitive innovation includes the repetition of existing design of existing products. Incremental innovation includes the creation of new design of existing products.
[2] Incremental innovation includes the development of new products to enter in new markets.

Codification of knowledge is needed to transfer knowledge easily and retain it in the firm, making it centrally available to organizational members (Sabherwal & Sabherwal, 2005). The process continues with the transfer and sharing of the knowledge among the organization's members and ends with knowledge application, which enables organizational members to propose initiatives based on that knowledge to solve operational problems and increase competitiveness (Alavi & Leidner, 2001).

Two critical concepts/phenomena from organizational learning should be highlighted: exploration and exploitation of knowledge. Knowledge exploration refers to the process of learning that helps the firm to acquire/create, share, assimilate, and store new knowledge. Knowledge exploitation is the process of learning that comes from reusing, transforming, applying, and leveraging existing/new knowledge in the firm (March, 1991).

The literature on knowledge exploration-exploitation management contains two divergent schools of thought, involving tradeoffs versus complementarity strategies. The tradeoff strategy advocates specializing in either searching for and acquiring new knowledge (e.g., exploration) or controlling and improving existing/new knowledge (e.g., exploitation) (March, 1991). Firms that prioritize exploitation are less able to adapt to changes, while firms that focus on exploration can lose efficiency because they cannot cover every new idea. Ambidexterity was born as the idea of simultaneously pursuing and balancing exploratory and exploitative practices to achieve better business performance. Ambidexterity theory thus considers exploration and exploitation as complementary strategies (Gupta et al., 2006; Kristal et al., 2010). Some scholars, such as Uotila et al., (2009) and Kim et al., (2012), analyze the tension and tradeoffs between exploitation and exploration implementation. Others examine the effect of ambidexterity on performance (e.g., Lubatkin et al., 2006). Lubatkin et al., (2006) examine whether a small-to-medium-sized firm's joint pursuit of exploration and exploitation enhances its performance. He and Wong (2004) study how exploration and exploitation can jointly affect firm performance in the context of technological innovation.

This investigation differs from prior research on IT, knowledge management, and firm performance by focusing on knowledge ambidexterity, the firm's ability to use a well-balanced combination of exploration and exploitation of organizational knowledge for operational purposes (e.g., Durcikova et al., 2011; He & Wong, 2004)[3]. Table 2.3 presents our comprehensive analysis of prior literature on organizational ambidexterity.

[3] Although knowledge sharing may be a component of knowledge exploration and knowledge reusing may be a component of knowledge exploitation, knowledge ambidexterity is a more complex concept than simply sharing and reusing knowledge. Knowledge exploration refers to the process of learning that helps the firm to acquire/create, share, assimilate, and store new knowledge. Then, knowledge exploration includes more things apart from sharing knowledge (i.e., acquisition/creation and store knowledge). Knowledge exploitation indicates the process of learning that comes from reusing, transforming, applying, and leveraging existing/new knowledge in the firm (March, 1991). Then, knowledge exploitation includes reusing knowledge, but also includes transforming, applying, and leveraging existing/new knowledge.

Table 2.3: Comprehensive analysis of prior research on organizational ambidexterity

Authors	Source	Key finding(s)
Tushman and O'Reilly (1996)	California Management Review	Superior firm performance is expected from ambidextrous firms, which simultaneously pursue incremental and discontinuous innovation. To become ambidextrous, it is essential that the firms have a decentralized structure, a common culture, and a supportive leadership
Gibson and Birkinshaw (2004)	Academy of Management Journal	The firm's context affects ambidexterity (the ability to achieve both alignment and adaptability simultaneously), which in turn affects performance
He and Wong (2004)	Organization Science	The interaction between exploratory and exploitative innovation strategies is positively related to sales growth rate
Gupta et al., (2006)	Academy of Management Journal	Theoretical paper addressing four issues: definitions and connotations of exploration and exploitation, orthogonality versus continuity, ambidexterity versus equilibrium, and duality versus specialization
Lubatkin et al., (2006)	Journal of Management	Managerial behavioral integration is essential to achieving ambidextrous orientation in small-to-medium-sized firms. Joint pursuit of an exploratory and exploitative orientation positively affects firm performance
Raisch and Birkinshaw (2008)	Journal of Management	This theoretical paper on the evolution of business ambidexterity research provides a synthesis of organizational ambidexterity research and areas for future research
Durcikova et al., (2011)	Information Systems Research	In a culture of innovation with absence of knowledge management systems, analysts are more able to reuse solutions (exploit) than to explore new solutions. The opposite occurs in a climate of autonomy, where analysts are more likely to innovate (explore) than to reuse solutions. In the presence of knowledge management systems, innovation culture enhances solution innovation, and a climate of autonomy diminishes it
Patel et al., (2013)	Academy of Management Journal	A complementary set of human resource management practices enables a high-performance work system that helps to develop the resource flexibility necessary to produce ambidexterity to increase firm growth
Voss and Voss (2013)	Organization Science	Strategies based on product and market exploration, product and market exploitation, and a combination of market exploration and product exploitation positively affect firms' revenues

2.3. Theory and hypotheses

2.3.1. IT-enabled organizational capabilities and the organizational learning framework

The IT-enabled organizational capabilities perspective argues that IT enables firms to generate business value through intermediate organizational capabilities such as flexibility, supply chain integration, talent management, organizational learning, and knowledge management (e.g., Ajamieh et al., 2016; Benitez et al., 2015; Benitez et al., 2018). For example, Chen et al., (2017) examine the impact of IT on firm performance through strategic flexibility. They find that IT support for core capabilities positively affects strategic flexibility to increase firm performance. This work draws on the IT-enabled organizational capabilities literature to theorize that firms that develop IT infrastructure capability and leverage it to explore and exploit organizational knowledge can generate significant innovation performance gains.

Organizational learning is one of the theoretical frameworks used in prior research to conceptualize and explore organizational ambidexterity (e.g., Raisch & Birkinshaw, 2008). Organizational learning is the dynamic process of creating knowledge through individuals' and groups' interaction to pursue organizational renewal (Crossan & Berdrow, 2003). This process requires creating new knowledge, explaining and codifying the new knowledge, sharing and transferring this knowledge within the firm, and embedding this knowledge through rules, norms, procedures, and forms. The resulting organizational knowledge is diffused to individuals to be leveraged (March, 1991). Exploration and exploitation are differentiated by the level of learning (e.g., Benner & Tushman, 2003; Gupta et al., 2006). A well-balanced combination of organizational knowledge exploration and exploitation (i.e., types of learning) helps to achieve long-term business benefits (Raisch & Birkinshaw, 2008). We use the organizational learning framework to conceptualize knowledge ambidexterity and explain how knowledge ambidexterity can lead to better innovation performance.

2.3.2. IT infrastructure and knowledge ambidexterity

IT infrastructure capability is the firm's ability to leverage its technical and human IT resource infrastructure (Benitez & Ray, 2012; Benitez et al., 2018; Melville et al., 2004) to acquire/provide accurate and timely information from/to key organizational members (Mithas et al., 2011; Pavlou & El Sawy, 2006). Based on Melville et al.,'s (2004) theoretical framework, IT infrastructure includes two components: technical IT resource infrastructure and human IT resource infrastructure. Technical IT resource infrastructure includes servers, computers, laptops, operating systems, software, electronic communication networks (email, Intranet, Extranet, and wireless devices), and shared customer databases (Aral & Weill, 2007; Benitez & Ray, 2012). Human IT resource infrastructure refers to the IT and business skills of IT managers and employees (Benitez et al., 2018; Byrd & Turner, 2001).

IT infrastructure can enable knowledge ambidexterity in the firm. First, IT infrastructure can affect knowledge exploration. The ability to acquire/share information from/to the market enabled by IT infrastructure can facilitate acquisition/creation of new organizational knowledge. IT technical and human resource infrastructure supports the firm to manage information better and facilitates the conversion of information into useful new knowledge (Mithas et al., 2011), enabling knowledge exploration. For example, Google continuously collects a huge amount of web-based market data (i.e., knowledge) for analysis. Based on this new knowledge, Google makes accurate predictions about the market (Coles et al., 2007).

IT infrastructure capability also helps the firm to internally share new knowledge through interpersonal relationships (Pavlou & El Sawy, 2006). IT improves communication within the firm. This is the case of Ernst and Young's Intranet, where consultants have online discussions, providing immediate access to collective knowledge (Lara et al., 2010). IT infrastructure capability can help the firm to store and assimilate new knowledge. IT infrastructure facilitates information update (e.g., identifying industry trends, customer interests, or competitor movements) (Joshi et al., 2010). By facilitating access to stored information enhances interpretation and synthesis of information, thus enabling knowledge exploration (Pavlou & El Sawy, 2006).

Second, IT infrastructure can enable knowledge exploitation in the firm. IT infrastructure provides the firm with IT tools to improve both coordination of the supply chain (i.e., upstream suppliers and downstream customers) and flexibility to reuse, transform, apply, and leverage new/existing organizational knowledge rapidly (Chen et al., 2017), enabling knowledge exploitation. In addition, IT infrastructure improves intra-firm coordination by enabling cross-functional collaboration within the firm (Kettinger et al., 2015) to facilitate knowledge exploitation. For example, Mercadona (a leading Spanish retailer) often leverages its technical IT resource infrastructure to better coordinate its new product development unit to convert a sensed potential customer need (i.e., market and customer knowledge) into a potential new product development (i.e., knowledge transformation and application, or knowledge exploitation) (Benitez et al., 2015).

In summary, IT infrastructure facilitates the acquisition and management of information both inside and outside the firm, facilitating acquisition/creation of new useful knowledge, and more efficient application and leveraging of the new/existing knowledge. Hence, it is rational to hypothesize that:

Hypothesis 1 (H1): There is a positive relationship between IT infrastructure and knowledge ambidexterity.

2.3.3. Knowledge ambidexterity and innovation performance

Innovation performance refers to the outcomes of the process of making changes in existing products/processes and/or to the development of new products/processes arising from internal and external knowledge (De Souza et al., 2016; Joshi et al., 2010; Kleis et al., 2012).

Knowledge ambidexterity can facilitate innovation performance. Overall, knowledge capabilities help the firm to understand complex technical knowledge, contributing to creation of new innovations (e.g., Joshi et al., 2010). Ability to innovate may in fact be considered as one of the critical contributions of knowledge management (e.g., Busquets, 2010) which may develop from knowledge ambidexterity. Ambidextrous firms can continuously improve current processes and obtain novel alternatives (Raisch & Birkinshaw, 2008), as ambidextrous new product teams are more efficient and better able to understand the market more quickly, enhancing the effectiveness of new product development tasks (e.g., Lubatkin et al., 2006). Thus, firms that both explore and exploit can maximize their innovations (Kim et al., 2012).

Knowledge exploration can improve innovation performance. Acquisition/creation and sharing of new knowledge within/beyond the firm's boundaries brings more new knowledge elements into the firm, increasing the potential number of architectural innovations (Henderson & Clark, 1990). For example, the interaction and collaboration of different backgrounds and expertise among supply chain partners enable the firm to acquire new knowledge to develop new products (Schoenherr et al., 2014). This capability can propel creative thinking and idea sharing in the firm, improving innovation performance (e.g., Lubatkin et al., 2006). Moreover, exploration enables access to different technological areas, adding diversity and heterogeneity that aid in new knowledge creation, and this new knowledge may be used to create more impactful innovations.

On other hand, firms that reuse, apply, and leverage existing/new knowledge (i.e., knowledge exploitation) better can outperform competitors in terms of more effective changes in existing products/processes, improving the firm's innovation performance. Using the same knowledge repeatedly increases the level of experience and understanding of the product's requirements, facilitating the task of product development (Eisenhardt & Tabrizi, 1995). Repeated use of knowledge elements also allows better assimilation and identification of the firm's valuable knowledge (i.e., knowledge identification), a critical antecedent to applying and leveraging knowledge, which may in turn positively affect innovation results (e.g., Katila & Ahuja, 2002).

Finally, prior empirical research finds that a firm's exploration and exploitation capabilities have a positive impact on new product development (Gupta et al., 2006; Newell, 2015). A clarifying example is how Nivea (a leading global skin care firm) explores and exploits knowledge to increase its innovation performance. Nivea has conducted sessions to acquire new knowledge from customers and experts on different topics, such as the problem of deodorants that stain the clothes. These sessions resulted in an anti-stain innovation, a new impactful product "black and white deodorant" that does not stain clothes. The firm analyzes data from existing sources, structuring and translating the data into useful knowledge through mechanisms such as group discussions or brainstorming that have generated new customer-oriented products (Lakhani et al., 2014). We thus hypothesize the following relationship:

Hypothesis 2 (H2): There is a positive relationship between knowledge ambidexterity and innovation performance.

2.3.4. Business value of social media: The moderator role of social media capability

2.3.4.1. The moderator role of social media capability in the relationship between IT infrastructure and knowledge ambidexterity

Social media capability refers to the firm's ability to leverage the social media platforms of Facebook, Twitter, and corporate blogs to execute business activities (Braojos et al., 2015a). This investigation argues that the relationship between IT infrastructure and knowledge ambidexterity can be stronger in presence of social media capability; that is, social media capability can perform a positive moderator role in this relationship. Examining this role is the first way we explore how social media capability may potentially help the firm to create business value (i.e., impact innovation/firm performance).

Social media capability provides a vast amount of data on the market (customers and industry) that may be used to explore and exploit knowledge digitally. Social media provide a platform for organizational members to contact each other with continuous inflow and outflow of users (e.g., Ku et al., 2013), facilitating superior and faster information flows both within the firm and in interaction with suppliers and customers/the market (Sultan, 2013). Such large data, more visible communication, and superior information flows enabled by social media (Limaj et al., 2016) increase opportunities to leverage IT resources to explore and exploit new/existing knowledge. For example, organizational members can acquire customer insights/feedback (i.e., new knowledge) from the firm's Facebook and Twitter sites and better assimilate this new knowledge through the firm's databases and the enterprise resource planning system, enabling knowledge exploration.

In summary, firms with social media capability will capture fine-grained data on the market that can be integrated into the firm's IT infrastructure to explore and exploit knowledge for business benefits. It is thus rational to expect that IT infrastructure and social media capability can work together to explore and exploit knowledge:

Hypothesis 3a (H3a): Social media capability positively moderates the relationship between IT infrastructure and knowledge ambidexterity.

2.3.4.2. The moderator role of social media capability in the relationship between knowledge ambidexterity and innovation performance

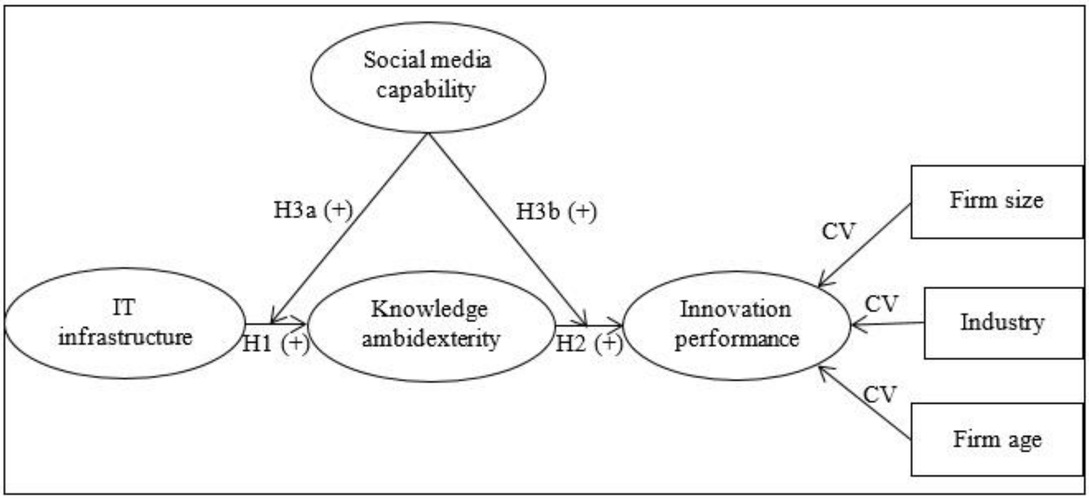
We argue that social media capability can also positively moderate the relationship between knowledge ambidexterity and innovation performance. This moderation is the second way we propose that social media capability may potentially help the firm to create business value. First, social media are valuable tools for managing knowledge effectively within firms (Sultan, 2013; Templeton et al., 2012), as they facilitate relationships and exchange of ideas, enhancing innovativeness (Kim et al., 2011). For example, Danone has implemented IT-based knowledge management programs (e.g., Who's Who and Dan 2.0), through which employees can interact in performing job tasks. Dan 2.0 is an internal social media platform that helps Danone to convert organizational knowledge into innovative solutions to solve problems, suggesting that social media capability reinforces the effect of knowledge ambidexterity on innovation performance. For example, when Danone launched biscuits in Finland, it did not know that Finns did not eat biscuits for breakfast. Thanks to IT-based knowledge sharing from LU France to LU Norway employees, the company repositioned the campaign to market the biscuit as a snack for mid-morning hunger, enabling Danone to maximize its marketing campaign (Beyersdorfer et al., 2011; Edmondson et al., 2008).

Second, social media empower the organization's members and customers to engage in the firm's knowledge management activities, enabling open innovation (Joshi et al., 2010). Such is the case of Siemens, which performed several knowledge-based open innovation projects both inside (with employees) and outside the firm (with suppliers and customers) using social media. One of these open innovation projects was run by OSRAM (a subsidiary of Siemens), which designed an open online contest that offered monetary prizes to participants with the best new and creative customer-oriented LED light solution. Participants could submit their ideas and evaluate or comment on other solutions. A total of 952 participants provided 576 ideas, ranging from children's toys to garden accessories. Finally, Siemens selected two of the 576 ideas and considered them for commercialization (Lakhani et al., 2015). In summary, since social media provide additional market data and knowledge to the firm on how to convert knowledge management efforts into more and better innovations, it is probable that ambidextrous firms will manage knowledge to transform new/existing knowledge into new products/processes more easily if they also have proficiency in social media.

We therefore hypothesize the following:

Hypothesis 3b (H3b): Social media capability positively moderates the relationship between knowledge ambidexterity and innovation performance.

Figure 2.1: Conceptual model (CV = Control variable)



2.4. Research methodology

2.4.1. Sample

We empirically tested the proposed model with a sample of the 100 small firms included in the 2013 Forbes America's Best Small Companies ranking (in short, the Forbes database), which includes the best 100 publicly recognized U.S. small firms with sales under one billion dollars (Braojos et al., 2015a). We analyzed all firms included in this ranking. The firms included in the sample came from 30 industries: consulting (18 firms), IT (16), food manufacturing (7), semiconductor manufacturing (6), healthcare (5), chemical (5), and other industries (43). Prior IS research contextualizes several types of studies of IT value in a sample of firms included in well-known rankings (like the ranking used in this study) (e.g., Benitez & Walczuch, 2012; Benitez et al., 2015; Bharadwaj, 2000; Braojos et al., 2015a; Joshi et al., 2010), confirming the logic of our decision.

This work focuses on small firms for two reasons. First, leveraging social media to explore and exploit knowledge remains crucial because small firms have a smaller portfolio of financial resources than large firms with which to compete effectively in the market (Braojos et al., 2015a). Second, prior research on IT, knowledge management, and innovation activities (e.g., Joshi et al., 2010) focuses on large firms. This work contributes to the field of IS by focusing on the moderator role of social media capability, a role not previously explored in similar research, and to do so by focusing on small firms.

2.4.2. Data and measures

To measure the constructs included in the proposed model, we collected and used a secondary dataset drawn from eight different databases. We first collected the data from the 2013 Forbes database and then used the name of each firm to gather information from the other databases.

4.2.1. IT infrastructure

Structured content analysis was performed of the firms' 2013 and 2014 annual reports collected from the U.S. Securities and Exchange Commission Filling database. The analysis measured IT infrastructure as a two-indicator composite[4] first-order construct composed of the accumulated total number of the firm's initiatives on mentions of technical and human IT resource infrastructure in 2013 and 2014 (Joshi et al., 2010; Luo et al., 2012). We used a list of 35 keywords on technical and human IT resources drawn from Braojos et al., (2015a, 2015b) and read the resulting paragraph carefully, computing each keyword—one per paragraph—where it appears (Table 2.4). Structured content analysis is a well-established method in IS research (e.g., Palvia et al., 2015).

[4] A clear distinction can be done between behavioral constructs and design artifacts (Henseler, 2017). While behavioral constructs are usually modeled as common factor models, composite-formative (in short, composite) should be the preferred choice for design artifacts. These artifacts can be understood as theoretically justified constructions which consist of more elementary components. They are human-made objects that are typically created by managers, staff, or the firm itself, and should be modeled as composite. The composite artifact serves as proxy for the concept under investigation and can be understood as a mix of ingredients (indicators/dimensions) forming the recipe (composite artifact) (Benitez et al., 2018; Henseler, 2015, 2017; Rueda et al., 2017). All the constructs/artifacts of this research were modeled as composite.

Table 2.4: List of initiatives/mentions on the firm's IT infrastructure

IT infrastructure component	References	Keywords
Technical IT resources	Aral and Weill (2007), Luo et al., (2012), Braojos et al., (2015a, 2015b)	Information technology (IT) Information system (IS) Computer/personal computer (PC) Laptop Operating system Data center Server Web/web site Network Internet Intranet Electronic media Online E-commerce/ecommerce E-mail/email Database/data Software Enterprise resource planning (ERP) Supply chain management (SCM)/SCM system Customer relationship management (CRM)/CRM system Data mining/data mining system Business intelligence
Human IT resources	Byrd and Turner (2001), Benitez and Ray (2012), Luo et al., (2012), Braojos et al., (2015a, 2015b)	IT IS IT manager/management Chief Information Officer (CIO) Chief Technology Officer (CTO) IT Vice President IT leadership IT skills IT expertise IT employee/worker/workforce Helpdesk IT training IT solution

2.4.2.2. Knowledge ambidexterity

Structured content analysis was also conducted to measure the knowledge ambidexterity construct. Joshi et al., (2010) provided a list of 18 critical keywords related to IT applications that enable knowledge management activities and measured knowledge management capability as the accumulated total number of a firm's IT applications that enable knowledge management activities, using information from the LexisNexis and Knowledge Management World databases. Knowledge Management World is a business magazine covering news on how IT is used to develop business knowledge activities/capabilities. We adopted the same measure scheme to measure knowledge ambidexterity with information from the LexisNexis and Knowledge Management World databases in 2013 and 2014. The coding process consisted of carefully reading the news on these 18 keywords published in 2013 and 2014, and deciding whether the firm used/applied the specific IT application or not, distinguishing between IT applications that helped the firm to acquire, share, assimilate, and store knowledge (i.e., to explore knowledge), and those that helped the firm to reuse, apply, and use organizational knowledge (i.e., to exploit knowledge) (Joshi et al., 2010). A total of 227 and 22 news items was identified for knowledge exploration and knowledge exploitation, respectively. Knowledge ambidexterity was measured as a two-indicator composite first-order construct determined by knowledge exploration and exploitation.

2.4.2.3. Social media capability

Social media capability was measured as a second-order construct determined by Facebook capability, Twitter capability, and blog capability (Braojos et al., 2015a, 2015b) with data collected in June 2014. Social media capability was specified as composite at both first- and second-order level.

We evaluated Facebook capability through a number of past or future events, experience, and updates using data collected from the firm's Facebook site. Following Braojos et al., (2015a), we measured the firm's experience on Facebook as the average number of months that the firm had operated on Facebook, and its updates by scoring, where 1 indicated a low and 5 a high degree of content updating in this platform. Each firm was given a score from 1 to 5 based on whether the firm had made a comment on Facebook more than one month ago/in the last month/in the last two weeks/in the last week/in the last two days, respectively.

Twitter capability was measured in terms of time spent writing tweets, experience, and updates using data collected from the firm's Twitter site and the Twopcharts database (http://twopcharts.com/). The time spent writing tweets was measured as the average hours that firm had spent writing tweets. Experience and updates were measured by the same method we used to measure Facebook. Blog capability was measured through the firm's experience and updates on blogs with data collected from the firm's blog site.

2.4.2.4. *Innovation performance*

Innovation performance, the key endogenous variable in this work, was measured with information collected from the U.S. Patent and Trademark Office database in the period 2007-2014, as follows. First, we estimated a patent quality weighting ratio (PQWR) by dividing the number of citations received by the firm's patents for one year from subsequent patents within a three-year window by the number of patents it published in a year (Kleis et al., 2012). We used the three-year window to avoid vintage effects of older patents (Kleis et al., 2012). This procedure weighted the number of patents in a year by the number of citations that these patents had received in the following three years, providing a patent measure that focuses on quality, not only number, of patents. We estimated a PQWR for 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014. For example, the 2007-2010 PQWR was estimated by dividing the number of citations received by the firm's 2007 patents from subsequent patents within the period 2008-2010 by the number of patents the firm published in 2007.

Second, based on these PQWR values, we built a ranking of firms by industry, in which a higher PQWR indicated a better position. We then calculated the rate of sectoral excellence (RSE) in innovation based on the firm's ranked position in its industry (Benitez & Walczuch, 2012; Benitez & Ray, 2012). RSE was estimated as follows: RSE = 1 - (Firm's position in its industry in our PQWR ranking / Total number of firms in each industry in our PQWR ranking). This procedure generated five indicators of RSE in innovation for 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014 for each firm included in the sample. These indicators were then used as five composite indicators to measure innovation performance (i.e., a first-order construct).

2.4.2.5. Control variables

We controlled for the effects of firm size, industry, and firm age on innovation performance with information collected from the 2013 and 2014 Forbes database. Firm size was measured as the natural logarithm of the average number of employees in 2013 and 2014 (Benitez & Walczuch, 2012). We measured industry as a dummy variable (0: Manufacturing firm, 1: Service firm). Firm age was measured as the natural logarithm of the number of years operating in its industry in 2014 (Chen et al., 2015).

2.5. Empirical analysis and results

We tested the proposed model empirically by using PLS path modeling, a variance-based SEM technique (Henseler et al., 2016; Marcoulides et al., 2009), with the statistical software package Advanced Analysis for Composites (ADANCO) 2.0 Professional (http://www.composite-modeling.com/) (Henseler & Dijkstra, 2015). ADANCO is modern software for variance-based SEM. It models composites, common factors, and single-indicator constructs and facilitates causal and predictive modeling (Benitez et al., 2017).

It is appropriate to use PLS in this research, first, because our constructs are specified as composite and PLS is particularly well suited to give consistent estimations for this type of model (Becker et al., 2013; Benitez et al., 2017; Henseler et al., 2014; Rigdon et al., 2014; Sarstedt et al., 2016). Second, PLS is particularly advisable for estimating models that employ secondary data, the case of our model (Gefen et al., 2011; Rigdon, 2013). Third, variance-based SEM techniques provide better results than covariance-based SEM techniques when estimating very complex models (i.e., those with multidimensional constructs) (e.g., Hair et al., 2012). PLS SEM has also been used widely in the field of IS (Ringle et al., 2012; Roldan & Sanchez, 2012).

Prior to data collection, we performed a statistical power analysis. The maximum number of predictors in the proposed model was six (the number of structural links received by innovation performance in the proposed model). Assuming a medium effect of size ($f^2 = 0.150$), the proposed model required a minimum sample size of 97 to achieve a power of 0.800 and an alpha level of 0.05 (Benitez et al., 2017; Cohen, 1988). Our sample size was 100, adequate to estimate the proposed model. This analysis suggested that our study had sufficient statistical power to detect the effect of interests (Benitez et al., 2017).

2.5.1. Measurement model evaluation

IT infrastructure, knowledge ambidexterity, and innovation performance are composite first-order constructs, whereas social media capability is a composite second-order construct. Composite constructs at first- and second-order level should be evaluated by assessing multicollinearity, weights, and loadings, as well as their level of significance (Benitez & Ray, 2012; Cenfetelli & Bassellier, 2009).

We evaluated the multicollinearity of our indicators/dimensions by estimating the variance inflation factors (VIF), which ranged from 1.112 to 16.041. All VIF values were below 3.3 except those of the construct IT infrastructure (16.041 in the two indicators), and two indicators of innovation performance. Based on the high correlation between these four indicators, we used the correlation weights (mode A) in the estimation of all constructs of the proposed model instead of the regression weights (mode B) to increase stability (Benitez et al., 2017).

A bootstrap analysis with 5000 subsamples (Petter et al., 2007; Barroso et al., 2010; Hair et al., 2011) showed that the indicator/dimension weights and loadings were significant for all constructs except for the weight of one indicator of innovation performance (i.e., RSE 2008-2011). This composite indicator was retained because its loading was significant (Benitez et al., 2017; Braojos et al., 2015b; Cenfetelli & Basellier, 2009).

Social media capability, a multidimensional construct, was estimated through the two-step approach (Chin, 2010). In the first step, we freely correlated all first-order constructs to obtain the latent variables scores of the dimensions. In the second step, the latent variables scores were used as the measures of the multidimensional construct (i.e., social media capability) (Wang et al., 2015). Table 2.5 shows the details of the measurement model properties.

Finally, we tested the external validity of all composites by conducting a confirmatory composite analysis of the saturated model (Benitez et al., 2017; Henseler et al., 2014; Henseler et al., 2016). Confirmatory composite analysis checks the adequacy of the composite models by comparing the empirical correlation matrix with the model-implied correlation matrix of the saturated model. This analysis can detect errors in assignment of indicators to constructs or in number of constructs (i.e., model misspecification) (Henseler et al., 2014). Table 2.6 shows the results for the first- and second-order models. Neither model should be rejected based on an alpha level of 0.05, since all discrepancies are below the 95%-quantile of the bootstrap discrepancies. These results suggest empirical support for this structure of composites at the first- and second-order levels. Overall, the proposed model presented very good measurement properties, implying that we could proceed with structural model assessment.

Table 2.5: Measurement model evaluation at first- and second-order level

Construct/dimension/indicator	Mean	S.D.	VIF	Weight	Loading
IT infrastructure	83.440	82.400			
IT infrastructure 2013	79.610	81.384	16.041	0.511***	0.992***
IT infrastructure 2014	87.270	83.638	16.041	0.497***	0.992***
Knowledge ambidexterity	1.525	5.684			
Knowledge exploration	2.580	7.761	1.412	0.622***	0.901***
Knowledge exploitation	0.470	1.573	1.412	0.516***	0.852***
Social media capability					
Facebook capability: Facebook activity of the firm in terms of:			2.352	0.426*	0.891***
Number of events	5.510	18.549	1.112	0.290***	0.564***
Experience	33.773	25.581	2.126	0.460***	0.893***
Updates	2.740	2.223	2.088	0.478***	0.890***
Twitter capability: Twitter activity of the firm in terms of:			2.622	0.358*	0.898***
Time spent writing tweets	17.280	32.149	1.307	0.315***	0.702***
Experience	35.752	27.651	2.114	0.457***	0.888***
Updates	2.750	2.285	2.254	0.417***	0.895***
Blog capability: Blog activity of the firm in terms of:			1.594	0.369*	0.810***
Experience	17.266	31.681	1.847	0.526***	0.909***
Updates	1.255	1.949	1.847	0.566***	0.922***
Innovation performance	0.146	0.298			
RSE 2007 - 2010	0.140	0.299	2.881	0.194*	0.806***
RSE 2008 - 2011	0.157	0.308	2.625	0.150	0.761***
RSE 2009 - 2012	0.143	0.299	4.577	0.258***	0.905***
RSE 2010 - 2013	0.122	0.278	6.948	0.251***	0.950***
RSE 2011 - 2014	0.167	0.309	2.966	0.295**	0.877***
Firm size: Natural logarithm of the total number of full-time employees	6.951	1.238			
Industry: Manufacturing vs. service	0.480	0.502			
Firm age: Natural logarithm of the number of years of the firm's operations	3.384	0.573			

Note: A two-tailed test was used for the statistical inference of weights and loadings.

Table 2.6: Results of the confirmatory composite analysis (saturated model)

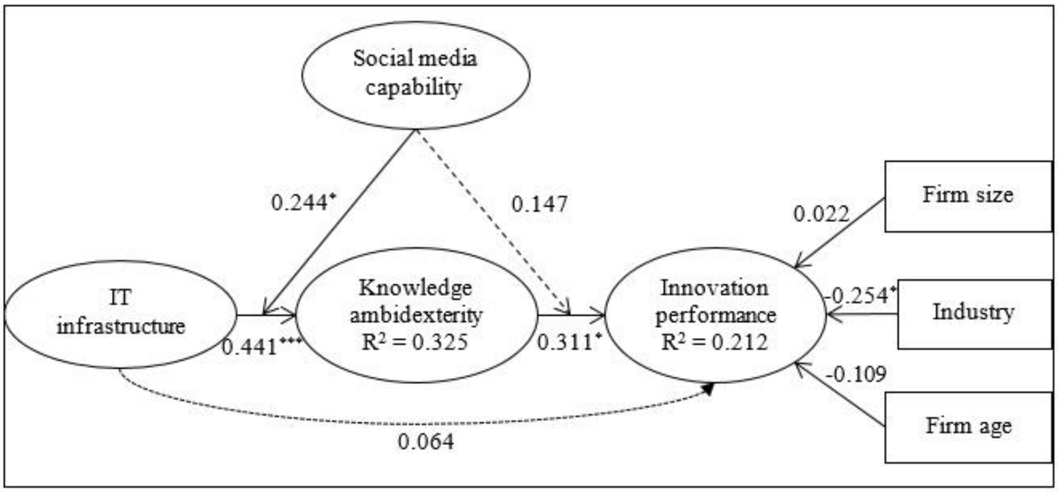
Discrepancy	First-order constructs			Second-order construct		
	Value	HI95	Conclusion	Value	HI95	Conclusion
SRMR	0.061	0.157	Supported	0.009	0.052	Supported
d_{ULS}	0.574	3.777	Supported	0.001	0.027	Supported
d_G	0.481	23.348	Supported	0.001	0.020	Supported

2.5.2. Structural model assessment

To test the hypothesized relationships, we evaluated the beta coefficients and significance of the proposed relationships (Henseler et al., 2016) by running a bootstrap analysis with 5000 subsamples. The effect size and R^2-values of the proposed relationships were also evaluated. We considered three models under study. To test the two first hypotheses (i.e., H1 and H2), we evaluated a baseline model that describes all direct effects on endogenous constructs, including all control variables and excluding social media capability. Model 1 includes in the prior model a link between social media capability and knowledge ambidexterity, and a link between social media capability and innovation performance. Model 2 adds the interaction terms to model 1 (Felipe et al., 2016) to test H3a and H3b. We find support for all proposed hypotheses except H3b. The empirical analysis suggests that IT infrastructure enables knowledge ambidexterity (H1) (β = 0.508, $p_{one\text{-}tailed} < 0.001$) and that this relationship is amplified more intensely when the firm leverages social media for operational purposes (H3a) ($\beta = 0.244$, $p_{one\text{-}tailed} < 0.05$), suggesting that social media capability plays a positive moderator role in this relationship. Similarly, knowledge ambidexterity increases innovation performance (H2) (β = 0.333, $p_{one\text{-}tailed} < 0.01$). Contrary to our expectations, the moderator role of social media capability in this relationship (H3b) is not significant ($\beta = 0.147$, $p_{one\text{-}tailed} > 0.10$, confidence interval: -0.326, 0.349). Future research on social media should explore this relationship. Table 2.7 and Figure 2.2[5] present the results of the test of hypotheses.

The R^2-values for these relationships were 0.258 and 0.177 for baseline model, 0.265 and 0.191 for model 1, and 0.325 and 0.212 for model 2. The effect size (f^2) values of the key relationships of the proposed model ranged from 0.100 to 0.348 for the baseline model, from 0.092 to 0.187 for model 1, and from 0.027 to 0.198 for model 2, indicating weak-to-large effect sizes between the exogenous and endogenous variables in the proposed theory (Henseler & Fassott, 2010). Table 2.7 presents an effect size analysis for all relationships included in the proposed model.

Figure 2.2: Results of the test of hypotheses



[5] Figure 2.2 presents the results of the model 2. 0.244* and 0.147 refer to the beta coefficients of the interaction terms between IT infrastructure and social media capability, and between knowledge ambidexterity and social media capability respectively. The effects from social media capability to knowledge ambidexterity ($\beta = 0.119$) and from social media capability on innovation performance ($\beta = 0.160$) have been omitted in this figure in sake of parsimony.

Goodness of model fit for the structural model was evaluated as in the confirmatory composite analysis described above, by examining the standardized root-mean-squared residual (SRMR), unweighted least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) for all models estimated (Benitez et al., 2017; Henseler et al., 2014). This measure of goodness of fit evaluates the discrepancy between the empirical correlation matrix and the model-implied correlation matrix of the estimated model(s) (Henseler, 2015). The lower the values, the better the fit between the proposed model and the data (Benitez et al., 2017; Benitez et al., 2018; Henseler & Dijkstra, 2015). Overall, the SRMR value should be lower than 0.080 to accept the fit between the proposed model and the data. All discrepancies should be below the 95%-quantile of the bootstrap discrepancies (Henseler et al., 2014). As the SRMR value of the proposed model was 0.059 and all discrepancies were below the 95%-quantile of the bootstrap discrepancies, the proposed model should not be rejected based on the alpha level of 0.05, which suggests very good model fit (see Table 2.7). Overall, the proposed model shows good structural model fit between the model and data (Henseler & Dijkstra, 2015). Table 2.8 presents the correlation matrix.

Table 2.7: Structural model assessment and test of robustness

Beta coefficient	Baseline model	Model 1	Model 2	Alternative model 1	Alternative model 2
IT infrastructure → Knowledge ambidexterity (H1)	0.508*** (6.330) [0.339, 0.661]	0.448*** (3.661) [0.184, 0.662]	0.441*** (4.152) [0.204, 0.612]		0.343* (2.263) [-0.016, 0.567]
Knowledge ambidexterity → Innovation performance (H2)	0.333** (2.533) [0.055, 0.572]	0.318* (2.274) [0.013, 0.564]	0.311* (1.960) [-0.073, 0.541]	0.306* (2.070) [-0.005, 0.579]	
IT infrastructure * Social media capability → Knowledge ambidexterity (H3a)			0.244* (1.960) [-0.056, 0.459]		0.236* (2.106) [-0.045, 0.436]
Knowledge ambidexterity * Social media capability → Innovation performance (H3b)			0.147 (0.750) [-0.326, 0.349]		
IT infrastructure → Innovation performance	0.147 (1.304) [-0.067, 0.375]	0.067 (0.568) [-0.170, 0.293]	0.064 (0.527) [-0.163, 0.319]	0.066 (0.544) [-0.171, 0.300]	
Social media capability → Knowledge ambidexterity		0.107 (1.023) [-0.042, 0.369]	0.119 (1.196) [-0.029, 0.363]		0.085 (0.765) [-0.088, 0.332]
Social media capability → Innovation performance		0.144 (1.158) [-0.097, 0.391]	0.160 (1.289) [-0.104, 0.390]	0.148 (1.127) [-0.126, 0.396]	
Firm size → Innovation performance	0.038 (0.441) [-0.130, 0.203]	0.036 (0.424) [-0.133, 0.198]	0.022 (0.255) [-0.134, 0.199]	0.032 (0.382) [-0.141, 0.188]	
Industry → Innovation performance	-0.292* (-2.344) [-0.513, -0.029]	-0.275* (-2.323) [-0.483, -0.024]	-0.254* (-2.081) [-0.490, -0.014]	-0.266* (-2.312) [-0.475, -0.027]	

Beta coefficient	Baseline model	Model 1	Model 2	Alternative model 1	Alternative model 2
Firm age → Innovation performance	-0.136 (-1.454) [-0.319, 0.049]	-0.122 (-1.339) [-0.298, 0.061]	-0.109 (-1.202) [-0.277, 0.074]	-0.122 (-1.323) [-0.291, 0.067]	
Knowledge ambidexterity → IT infrastructure				0.352*** (3.477) [0.148, 0.553]	
Knowledge ambidexterity * Social media capability → IT infrastructure				-0.036 (-0.322) [-0.196, 0.242]	
IT infrastructure * Social media capability → Innovation performance				0.037 (0.215) [-0.338, 0.281]	
Social media capability → IT infrastructure				0.434*** (5.308) [0.270, 0.594]	0.538*** (6.670) [0.376, 0.695]
Innovation performance → IT infrastructure					0.045 (0.425) [-0.163, 0.251]
Innovation performance * Social media capability → IT infrastructure					0.068 (0.644) [-0.197, 0.211]
Innovation performance → Knowledge ambidexterity					0.243* (2.289) [0.002, 0.413]
Firm size → Knowledge ambidexterity					-0.015 (-0.176) [-0.182, 0.152]
Industry → Knowledge ambidexterity					0.146 (1.253) [-0.035, 0.424]

Beta coefficient	Baseline model	Model 1	Model 2	Alternative model 1	Alternative model 2
Firm age → Knowledge ambidexterity					0.047 (0.765) [-0.072, 0.173]
R^2					
Knowledge ambidexterity	0.258	0.265	0.325		0.382
Innovation performance	0.177	0.191	0.212	0.192	
IT infrastructure				0.425	0.317
Discrepancy					
SRMR value	0.007	0.020	0.059	0.073	0.123
SRMR HI_{95}	0.048	0.049	0.117	0.101	0.098
d_{ULS} value	0.001	0.019	0.410	0.639	1.385
d_{ULS} HI_{95}	0.048	0.109	1.628	1.223	0.873
d_G value	0.000	0.013	0.396	0.491	0.324
d_G HI_{95}	0.018	0.080	1.013	0.833	0.507
f^2					
IT infrastructure → Knowledge ambidexterity (H1)	0.348	0.187	0.198		0.083
Knowledge ambidexterity → Innovation performance (H2)	0.100	0.092	0.090	0.078	
IT infrastructure * Social media capability → Knowledge ambidexterity (H3a)			0.088		0.086
Knowledge ambidexterity * Social media capability → Innovation performance (H3b)			0.027		
IT infrastructure → Innovation performance	0.013	0.002	0.002	0.002	
Social media capability → Knowledge ambidexterity		0.011	0.014		0.008
Social media capability → Innovation performance		0.017	0.021	0.018	
Firm size → Innovation performance	0.001	0.001	0.001	0.001	

Beta coefficient	Baseline model	Model 1	Model 2	Alternative model 1	Alternative model 2
Industry → Innovation performance	0.060	0.054	0.047	0.049	
Firm age → Innovation performance	0.018	0.015	0.012	0.015	
Knowledge ambidexterity → IT infrastructure				0.188	
Knowledge ambidexterity * Social media capability → IT infrastructure				0.002	
IT infrastructure * Social media capability → Innovation performance				0.002	
Social media capability → IT infrastructure				0.283	0.390
Innovation performance → IT infrastructure					0.003
Innovation performance * Social media capability → IT infrastructure					0.007
Innovation performance → Knowledge ambidexterity					0.084
Firm size → Knowledge ambidexterity					0.000
Industry → Knowledge ambidexterity					0.018
Firm age → Knowledge ambidexterity					0.003

Note: t-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square bracket (based on n = 5000 subsamples). $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on $t(4999)$, one-tailed test]. $t(0.05, 4999) = 1.645$; $t(0.01, 4999) = 2.327$; $t(0.001, 4999) = 3.092$ for hypothesized relationships. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on $t(4999)$, two-tailed test]. $t(0.05, 4999) = 1.960$; $t(0.01, 4999) = 2.577$; $t(0.001, 4999) = 3.292$ for non-hypothesized relationships.

Table 2.8: Correlation matrix

	1	2	3	3.1	3.2	3.3	4	5	6	7
1. IT infrastructure	1.000									
2. Knowledge ambidexterity	0.508	1.000								
3. Social media capability	0.557	0.358	1.000							
3.1. Facebook capability	0.453	0.303	0.891	1.000						
3.2. Twitter capability	0.464	0.292	0.898	0.751	1.000					
3.3. Blog capability	0.536	0.332	0.810	0.532	0.597	1.000				
4. Innovation performance	0.180	0.335	0.252	0.891	0.898	0.209	1.000			
5. Firm size	0.159	0.106	0.052	0.061	0.071	0.001	-0.026	1.000		
6. Industry	0.612	0.321	0.272	0.250	0.215	0.238	-0.063	0.292	1.000	
7. Firm age	-0.271	-0.124	-0.235	-0.212	-0.181	-0.216	-0.161	0.278	-0.156	1.000

2.5.3. Mediation analysis

Mediation analysis was performed to examine whether the indirect effects involved in the proposed model were significant. This analysis estimated and analyzed the indirect effect in the baseline model (i.e., the link between IT infrastructure and innovation performance), to explore if the indirect effect was significant (Table 2.9) (Nitzl et al., 2016; Zhao et al., 2010). The indirect effect was significant at 0.05 level while the direct effect was not significant, which suggests a full mediation of knowledge ambidexterity in the impact of IT infrastructure on innovation performance (Nitzl et al., 2016; Zhao et al., 2010). This model had very good fit (Table 2.7). These analyzes indicate that IT infrastructure influences innovation performance through knowledge ambidexterity.

Table 2.9: Mediation analysis (baseline model)

Relationship	Direct effect	Indirect effect
IT infrastructure → Innovation performance	0.147 (1.304) [-0.067, 0.375]	0.169* (2.076) [0.026, 0.343]

2.5.4. Test of robustness

We tested the robustness of the proposed model by estimating two alternative/competing models. In the first alternative model, we assumed that knowledge ambidexterity affects development of an IT infrastructure capability, which in turn may affect innovation performance, preserving the moderating role of social media capability. This alternative model's beta coefficients ranged from -0.036 to 0.352***, lower than those of our proposed model. Neither of the two interaction effects was significant. In the second alternative model, we considered innovation performance to affect knowledge ambidexterity through IT infrastructure, retaining the moderating role of social media capability. In this model, the beta coefficients were also lower than in our proposed model and ranged from 0.045 to 0.343***. To compare these alternative models to our proposed model, we also compared the overall fit of the baseline model and model 2, and the overall fit of the two alternative models (Braojos et al., 2015b; Henseler et al., 2014; Henseler, 2015). The two alternative models had higher SRMR values (0.073 and 0.123) and worse overall fit between model and data, suggesting that the proposed theory was the best and most rational explanation of our data (Braojos et al., 2015a).

2.5.5. Post-hoc multi-group analysis: Firms with low social media capability vs. firms with high social media capability

We performed a post hoc multi-group analysis to explore whether there were statistically significant differences between firms with low versus high development of social media capability relative to the effects included in the proposed model (Table 2.10). The calculations are based on the equation (1) described in Sarstedt et al., (2011). We found differences between these firms in the relationship between IT infrastructure and knowledge ambidexterity, reinforcing the support for H3a. As before, the analysis did not support H3b.

Table 2.10: Post-hoc multi-group analysis

Coefficient	Firms with low social media capability (N = 53)	Firms with high social media capability (N = 47)	Was the difference in the beta coefficient statistically significant?
IT infrastructure → Knowledge ambidexterity (H1)	0.099 (0.677) [-0.056, 0.504]	0.523*** (5.553) [0.330, 0.700]	Yes ($p < 0.01$)
Knowledge ambidexterity → Innovation performance (H2)	0.341** (2.369) [0.043, 0.671]	0.424** (2.440) [0.055, 0.753]	No (not significant)
IT infrastructure → Innovation performance	0.266† (1.643) [0.012, 0.643]	0.055 (0.245) [-0.448, 0.415]	No (not significant)
Firm size → Innovation performance (control variable)	0.193 (1.521) [-0.012, 0.494]	-0.055 (-0.420) [-0.330, 0.192]	No (not significant)
Industry → Innovation performance (control variable)	-0.351** (-2.862) [-0.593, -0.108]	-0.368 (-1.426) [-0.784, 0.225]	No (not significant)
Firm age → Innovation performance (control variable)	0.024 (0.171) [-0.283, 0.261]	-0.283* (-2.219) [-0.506, 0.004]	No (not significant)

2.6. Discussion and conclusions

2.6.1. Implications and key contributions to IS research

This research examines the impact of IT infrastructure on knowledge ambidexterity and innovation performance, and the potential moderator role of social media capability in this equation. The proposed theory was tested on a sample composed of 100 small U.S. firms, and the empirical analysis suggests that IT infrastructure enables the firm to explore new knowledge and exploit existing/new knowledge to innovate more and better. We find that IT infrastructure capability influences innovation performance through knowledge ambidexterity. The analysis also suggests that social media capability plays a moderator role in this equation: IT infrastructure and social media capabilities work together to enable knowledge ambidexterity. The empirical analysis thus supports a significant portion of our theory.

This research makes three contributions to the field of IS. First, with a few exceptions (Eseryel, 2014; Joshi et al., 2010), research on the impact of IT on knowledge management and innovation activities *in the same study* is very limited. Our paper provides new evidence on how IT infrastructure enables exploration and exploitation of organizational knowledge to increase innovation performance. Unlike prior IS research, we focus on knowledge ambidexterity in small firms, drawing on prior literature on organizational ambidexterity to conceptualize knowledge ambidexterity. The ability to simultaneously pursue and balance exploration and exploitation of knowledge for operational purposes (i.e., knowledge ambidexterity) may be an even more critical capability for small firms due to their greater challenge to survive in the long run.

Second, this investigation develops the concept of social media capability for business activities (beyond marketing activities), and theorizes how this capability moderates the relationships between IT infrastructure and knowledge ambidexterity. Study of firms' use of social media for business activities is in the initial stages (Braojos et al., 2015a, 2015b). The field of IS really needs theories and empirical studies that explain whether and how social media capabilities help firms to create business value. We take a first step toward this goal by explaining and demonstrating that social media capability creates business value by amplifying the impact of leveraging technical and human IT resources to explore and exploit knowledge for operational purposes. This creation of business value is an indirect effect on firm performance by reinforcing the effect of IT infrastructure on knowledge ambidexterity to improve innovation performance.

Third, this work argues that social media constitute a complementary IT capability that complements the relationships between IT and organizational capabilities. Complementary capabilities refer to the mutual reinforcement of two activities such that the presence of one increases the value of the other (Ennen & Richter, 2010). IT infrastructure and social media reinforce each other to explore and exploit organizational knowledge. The third theoretical contribution of this research is to suggest the role of social media as a complementary capability that help firms to maximize the value created from IT-enabled organizational capabilities. This argument has clear theoretical implications for developing both perspective on IT-enabled organizational capabilities (e.g., Tanriverdi, 2005) and the literature on complementary capabilities (e.g., Ennen & Richter, 2010). This insight suggests that the cumulative base of IT capabilities (i.e., IT infrastructure and social media) is central because these capabilities are complementary. This theoretical advance has serious implications for future IS research on IT capabilities and the intermediate organizational capabilities derived from IT. Future IS research should investigate why and how some firms develop a cumulative base of IT capabilities more quickly than others. Future research could also investigate the complementary role of social media capability in the effect of IT on development of organizational capabilities. These are very promising avenues for future IS research.

2.6.2. Limitations and future research directions

This research has also some limitations. First, our findings can be only generalized to small firms in the U.S. market. We have not explored whether the proposed theoretical model is supported in samples of small firms of other markets (e.g., the European Union, Latin America, and Asia). Second, we focused on a sample composed of firms from 30 industries. Although we controlled for industry, the proposed theory may behave very differently from industry to industry. Future research might explore our theory focusing on service industries with high IT investments and/or on firms/customers that are more active in social media. Third, we analyzed three of the most popular external social media sites but did not examine the role of internal social media capabilities. Finally, two of our variables (IT infrastructure and knowledge ambidexterity) were measured through structured content analysis, a well-accepted technique for collecting secondary data but one that may have some bias. Although we measured knowledge ambidexterity based on the well-established measurement scheme of Joshi et al., (2010), and although clear discriminant validity exists between the constructs IT infrastructure and knowledge ambidexterity[6], there may be some bias related to the "IT-enabled" emphasis of our measure of knowledge ambidexterity. Future IS research

[6] The correlation between IT infrastructure and knowledge ambidexterity was moderate (0.508***). Analysis of the Fornell-Larcker criteria, heterotrait-monotrait ratio of correlations, and indicator cross-loadings between IT infrastructure and knowledge ambidexterity suggested clear discriminant validity between IT infrastructure and knowledge ambidexterity (Henseler et al., 2016). Additionally, we removed the data on measures that might overlap in the measures of IT infrastructure and knowledge ambidexterity and re-estimated the baseline model, which led to almost identical results.

should revisit or extend our theory by designing and using survey measures of IT infrastructure and knowledge ambidexterity.

2.6.3. Implications for managers

The findings of this research provide two critical lessons for IT managers. First, leveraging IT technical and human resource infrastructure provides the foundation to explore and exploit market and product knowledge, ultimately to change/develop better products/processes. Leveraging IT infrastructure improves coordination within the firm and the supply chain, which in turn facilitates the firm's ability to acquire, sense, apply, and leverage knowledge for innovation benefits. Second, firms can differentiate themselves in the market if they invest and leverage Facebook, Twitter, and corporate blogs for business activities, that is, if they develop social media capability. Firms with social media capability will capture fine-grained data on the market that can be integrated into the firm's IT infrastructure to explore and exploit knowledge for business benefits. In the cumulative effect of IT infrastructure and social media capabilities, the whole is greater than the sum of its parts. IT infrastructure and social media are mutually reinforcing in the exploration and exploitation of organizational knowledge. We are confident that these lessons will help IT managers to create business value from their IT/social media investment decisions.

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IMPACT OF SOCIAL MEDIA ON INNOVATION PERFORMANCE: THE ROLES OF KNOWLEDGE AMBIDEXTERITY AND BUSINESS ANALYTICS TALENT

3

3. IMPACT OF SOCIAL MEDIA ON INNOVATION PERFORMANCE: THE ROLES OF KNOWLEDGE AMBIDEXTERITY AND BUSINESS ANALYTICS TALENT

Abstract

We propose an organizational theory of social media and innovation that emphasizes the roles of knowledge ambidexterity and business analytics talent. We tested our proposed theory on a sample of U.S. firms. The results of the empirical analysis suggest that social media capability enables firms to effectively achieve exploration and exploitation of knowledge (i.e., knowledge ambidexterity), which in turn increases innovation performance. Business analytics talent plays a positive moderator role on these relationships. This study provides an organizational theory on social media and innovation by drawing on the lens of knowledge ambidexterity and business analytics talent.

Keywords: Social media capability, knowledge ambidexterity, innovation performance, business analytics talent.

3.1. Introduction

Business analytics talent is the firm's talent in effectively applying business analytics at firm level by transforming data into valuable insights for supporting business activities (Ransbotham et al., 2015). Firms with business analytics talent are able to perform effectively business analytics to turn analytical insight into business actions. Firms effectively performing business analytics go from descriptive analytics to determine what occurred in the past, and what occurs now and why, through predictive analytics to model what will happen in the future, to prescriptive analysis to develop multiple options about the future and help decide what to do (Ransbotham et al., 2015). Despite its potential business value, according to McKinsey Global Institute, in 2018 there will be a lack of business analytics talent in U.S., which is expected to be about 140000 to 190000 analytics talented people, and a lack of 1.5 million managers and analysts with the appropriate abilities to understand and make decisions (Ransbotham et al., 2015). In this sense, business analytics talent is a scarce and a valuable information technology (IT) resource among contemporary companies. Perhaps, this may explain why a large amount of the Information Systems (IS) academic jobs in the job market of the last years has dramatically demanded academic expertise in business analytics.

In a similar way, valuable knowledge management activities have been considered a strategic issue that enables firms to survive in the long run (Lara et al., 2010), because organizational knowledge is a resource difficult to imitate, which may explain a significant portion of firm performance variation, and be a source of competitive advantage for firms (Alavi & Leidner, 2001; Soto et al., 2016). Well-known firms, such as Capgemini and Ernst & Young consider their knowledge management activities as critical. They are two good examples of companies that have leveraged their knowledge management activities to satisfy customer's needs and increase firm's sales (Benitez et al., 2018a).

Firms need to collect, monitor, and analyze data to achieve greater business value (He et al., 2015). Social media platforms are considered as one of the most popular online communication tools and source of information for both individuals and firms (Benitez et al., 2018a; Chai et al., 2011; Luo et al., 2015). Social media platforms can be considered as facilitators of knowledge and potential sources of innovation (Leonardi, 2014). Firms can use social media (e.g., Facebook, Twitter, corporate blogs) to communicate their products and initiatives, and to relate with customers. Specifically, firms run social media campaigns to build awareness about their products or initiatives, and to test them by collecting opinions, impressions, and ideas from customers (Dong & Wu, 2015). Thus, social media provide a vast amount of customer and competitor data that can be leveraged by the firm to innovate (Aral et al., 2013; Benitez et al., 2018a). For example, Lay's (a potato chip manufacturer) ran a campaign in social media (Facebook, Twitter, Instagram) called "Do us a flavor". This campaign aimed to innovate about the next potato chip flavor, collecting ideas from their customers. Four finalist flavors were sold provisionally, and then customers voted in social media for the best one, being Southern Biscuits and Gravy flavor eventually sold. However, generating and collecting social data is not enough to make an efficient use of information. Monitoring, analyzing, and identifying relevant social media-based information is critical in transforming information into business gains. Ransbotham et al. (2015) suggested that using social data effectively may be critical to support business activities. The process of changing data into valuable insights to support business activities is called "business analytics" (Chen et al., 2012; Holsapple et al., 2014). Business analytics refers to the support of decisions making and problem resolution into the firms through two main capabilities: "speed to insight" (i.e., how fast firms can transform social data into insight), and "pervasive use" (i.e., deep usage of business analytics across the firm) (Wixom et al., 2013). In this sense, firms face to the challenge of hiring, developing, and retaining business analytics talent to transform social data into valuable insights for supporting business activities. As a scarce and valuable resource, business analytics talent may explain some variation in performance among contemporary firms (Ransbotham et al., 2015).

Prior IS research has mainly focused on analyzing the IT impact on knowledge management and performance (Joshi et al., 2010; Tanriverdi, 2005). Few studies have examined the motivations of employees and customers to share knowledge in the firm's social media platforms (e.g., Beck et al., 2014; Leonardi, 2014). For example, Chai et al. (2011) identified factors which have a positive effect on knowledge sharing of bloggers. However, IS research lack of an organizational theory of social media initiatives, firm's knowledge management activities, and innovation results (Dong & Wu, 2015; Ngai et al., 2015). How do social media initiatives affect knowledge management and innovation activities? This study tries to fill this gap and answer this question.

Firms may invest in effectively managing social media to acquire and exploit social data to improve their business processes and products (i.e., innovation). For example, Dell created a social media platform (http://www.ideastorm.com/) to acquire and exploit data from their customers, enabling them to submit their ideas, vote for other ideas, and comment on ideas of other customers. Dell managed customers' data to implement the best ideas (e.g., biodegradable packing material), which led to product and process innovations. In this sense, the innovation outputs are an excellent return on investment in social media management for a firm (Dong & Wu, 2015). This leads to the first research questions of this study 1) Does social media capability (i.e., firm's ability to leverage social media platforms to execute business activities) impact on innovation performance through knowledge ambidexterity (i.e., the firm's ability to efficiently achieve exploration and exploitation of organizational knowledge simultaneously for operational purposes)? This sequence of effects should be stronger in those firms that additionally transform social data into useful social knowledge through business analytics talent (Davenport et al., 2010; Ransbotham et al., 2015). For example, GUESS (i.e., a fashion retailer) implemented business analytics initiatives through GMobile project (iPad-based app). This GMobile app generated transactional innovative benefits (e.g., reducing paper costs, increasing eco-friendliness, spending less time finding answers…), informational innovative benefits (e.g., more and better information improving decisions), and strategic innovative benefits (e.g., better understanding of the business model, and purchasing and distribution decisions) (Wixom et al., 2013). This leads to the second research question of this paper: 2) Can these relationships be strengthened when business analytics talent comes into play?

We theorize that social media capability can enable firms to explore and exploit knowledge, which in turn can improve firm's innovation performance, and that firms with more and better business analytics talent can amplify and strengthen these relationships. This is the central theoretical proposition of this manuscript. We tested this organizational theory using partial least squares (PLS) path modeling with a secondary dataset on a sample of U.S. firms. The empirical analysis gives substantial support to the postulated theory.

This study provides an organizational theory of social media and innovation that has several contributions to the field of IS. First, this paper develops the concept of social media capability, explains theoretically, and shows empirical evidence on how firms can create business value from social media capability. Second, this study develops the concept of business analytics talent, and shows how this capability positively moderates the relationships between social media capability and knowledge ambidexterity, and between knowledge ambidexterity and innovation performance.

The rest of the paper is organized as follows. Next section presents the theoretical background and the hypotheses development that explains the proposed organizational theory. The research methodology section explains the sample, data and measures of this study. After that, the empirical analysis, the results, and findings are presented in the empirical analysis section. The paper concludes with a discussion of the findings and suggestions for future research.

3.2. Theory and hypotheses

3.2.1. Organizational capabilities-based theory, IT-enabled organizational capabilities, organizational learning framework, and the complementary resource perspective

The organizational capabilities-based theory suggests that firms design and execute IT and business strategies based on their portfolio of organizational capabilities, which explains the difference in competitiveness among firms (Grant, 1996). Organizational capabilities[7] can be classified into: dynamic capabilities (firm's proficiency in adapt its resource base in response to changes in the business environment) (Benitez et al., 2018b; Teece, 2007); operational capabilities (firm's proficiency in solving operational problems and implementing the operations strategy by using interrelated operational routines) (Benitez et al., 2018c; Wu et al., 2010); and dual-purpose capabilities (organizational capabilities that are dynamic and operational capabilities because they can be controlled and exploited at both strategic and operational level) (Benitez et al., 2018b; Helfat & Winter, 2011). We use organizational capabilities-based theory to conceptualize social media capability, knowledge ambidexterity and business analytics talent, and to link social media capability to knowledge ambidexterity.

[7] Organizational capabilities can be IT and business capabilities. Business capabilities refer to the non-IT capabilities of the firm. In this sense, companies can develop dynamic, operational, and dual-purpose IT and business capabilities (Benitez et al., 2018b).

The IT-enabled organizational capabilities perspective has emerged as a solid theoretical base in the IS literature to explain the value creation from IT by arguing that IT helps firms to create business value through intermediate organizational/process capabilities. Some of these organizational capabilities are business flexibility (Benitez et al., 2018b; Benitez et al., 2018d; Chen et al., 2017), supply chain management (Ajamieh et al., 2016), corporate entrepreneurship (Chen et al., 2015), and new product development (Pavlou & El Sawy, 2006). As social media technology is a new type of digital technology, IT-enabled organizational capabilities theory provides a useful framework to theorize that social media capability influences innovation performance through knowledge ambidexterity.

Organizational ambidexterity theory posits that firms are ambidextrous when they can reconcile exploration and exploitation behaviors (March, 1991). Different literature streams have contributed to this topic (e.g., Technological and Innovation Management, Strategy, and Organizational Learning) (Raisch & Birkinshaw, 2008). Organizational learning refers to the process in which firms pursue organizational renewal through creation of knowledge, explaining, and codifying this knowledge, and sharing and transferring this knowledge within the firm to be used, and embedding them through rules and procedures (March 1991). We draw from organizational learning framework, which considers exploration and exploitation as two learning activities (Gupta et al., 2006), to conceptualize organizational ambidexterity hence building the concept of knowledge ambidexterity (Benitez et al., 2018a). Knowledge exploration is the learning process of acquiring/creating, sharing, and storing new knowledge, while knowledge exploitation is composed by the learning obtained from the process of assimilating, reusing, reinterpreting, applying, and leveraging new/existing knowledge (Gupta et al., 2006; March, 1991). Ambidextrous firms in knowledge management (knowledge ambidexterity) are those that efficiently achieve exploration and exploitation of organizational knowledge simultaneously for operational purposes (Benitez et al., 2018a; Levinthal & March, 1993; Tushman & O'Reilly, 1996). Achieving knowledge exploration and exploitation simultaneously may help firms to achieve long-term business benefits (Raisch & Birkinshaw, 2008). We also use organizational learning conceptual framework to explain theoretically how knowledge ambidexterity enables innovation performance.

The complementary resource perspective is a theoretical framework that states that the complementarity among resources of the firm explains the differential effect in firm performance. Complementary between resources/capabilities denotes the mutual reinforcing of the capabilities where the presence of a resource/capability allows other resources/capabilities exert their value (Ennen & Richter, 2010). These complementary relationships may drive firm performance, which may differ from the sum of the individual effects considered in isolation (Adegbesan, 2009; Bharadwaj et al., 2007; Ennen & Rithter, 2010). Our central proposition is that the positive effect of social media capability on knowledge ambidexterity, and the positive effect of knowledge ambidexterity on innovation performance can be amplified if the firm is business analytics talented. Thus, we use the complementary resource perspective to explain theoretically that business analytics talent complements social media capability and knowledge ambidexterity to explain variations in innovation performance.

3.2.2. Construct definition

3.2.2.1. Social media capability

Social media capability refers to the firm's ability to purposely use and leverage external social media platforms to execute business activities (Benitez et al., 2018a). This study considers three of the most used external social media platforms (i.e., Facebook, Twitter, and corporate blogs) by the contemporary firm (Culnan et al., 2010). Considering Fortune 500 firms in 2016, 84% used Facebook, 86% used Twitter, and 36% had corporate blogs. In 2017, 100%, 90%, and 80% of the top 10 of the U.S. Fortune 500 firms have Facebook, Twitter, and corporate blog respectively.

3.2.2.2. Knowledge ambidexterity: Knowledge exploration and knowledge exploitation

Knowledge exploration refers to the learning process of experimenting with new knowledge and business opportunities by acquiring/creating, sharing, and storing this new knowledge (March, 1991). Knowledge exploitation refers to the learning process of assimilating, reusing, reinterpreting, applying, and leveraging that existing/new knowledge (March, 1991). In the literature coexist two theories on the organizational viability to explore and exploit knowledge: as two extremes of a continuum (tradeoffs), or as two independent activities (complementary strategies) (Gupta et al., 2006). As two extremes of a continuum, exploration of new knowledge and the exploitation of existing knowledge are the two extremes of the same continuum (Rosenkopf &

McGrath, 2011), which advocates specializing/focusing in either exploration or exploitation (March, 1991). Of course, a company may be situated on an intermediate position instead of some of the extremes. Under this logic, the consideration of exploration and exploitation would be of the equilibrium.

As two independent activities (complementary strategies), knowledge exploration and exploitation are orthogonal and different learning activities differentiated by the level of learning (Gupta et al., 2006; He & Wong, 2004). Under this logic the concept of ambidexterity makes sense, as it is defined as the firm's ability to achieve both activities (exploration and exploitation) simultaneously (ambidextrous firms). Based on this second stream of ambidexterity literature, this manuscript defines knowledge ambidexterity capability as the firm's ability to efficiently achieve exploration and exploitation of organizational knowledge simultaneously for operational purposes (Gupta et al., 2006; Tushman & O'Reilly, 1996).

3.2.2.3. Innovation performance

Innovation performance refers to the outcomes of the process of changing existing products/processes and/or to the development of new products/processes (Benitez et al., 2018a; Joshi et al., 2010; Kleis et al., 2012).

3.2.2.4. Business analytics talent

Business analytics is a group of people, approaches, organizational procedures, and tools used in combination that convert data into insights for problem recognition and problem solving within the business situations context (Holsapple et al., 2014; Trkman et al., 2010; Wixom et al., 2013). We draw on the Ransbotham et al.'s (2015) work to conceptualize business analytics talent. Analytics talent refers to the talent of people on performing business analytics (i.e., appropriate analytical skills) to be able to create insights and apply them to strategic business activities. Thus, business analytics talent is defined in this study as the firm's ability in effectively applying business analytics at firm level by transforming data in valuable insights for supporting business activities (Ransbotham et al., 2015).

3.2.3. Social media capability and knowledge ambidexterity

Social media capability can facilitate knowledge ambidexterity of the firm. Overall, social media provide a platform which facilitates the communication among organizational members (Ku et al., 2013). Social media-enabled interaction between knowledge seekers and knowledge contributors facilitates the development of organizational knowledge (Beck et al., 2014). There is a lack of physical and social boundaries in online environments, which facilitates accessing and transferring/sharing of new knowledge, thus facilitating the exploration of new knowledge. Firms can use social media to acquire/share large amount of knowledge from/to market (suppliers, competitors, and customers) (Benitez et al., 2018a). For example, firms can leverage social media to create collaborative communities with suppliers, enabling a major acquisition of knowledge from them. Firms can also leverage social media to acquire knowledge on the competitor movement and activities (e.g., a supermarket chain that access to the key supplier base in the Twitter profile of its direct competitors).

Moreover, firms can also acquire new customer knowledge (e.g., preferences and feedback on the current firm's products, or ideas for new product development) from the firm's social media (e.g., Facebook and Twitter), and also share knowledge with customers (e.g., new product launching), thus enabling knowledge exploration. For instance, Mercadona (i.e., leading Spanish supermarket chain), has used actively its Twitter profile to acquire new customer knowledge (i.e., knowledge exploration). Thanks to the knowledge contribution from customers on Twitter, Mercadona has known the lack of stock of specific products in specific stores (e.g., customer complain on Twitter about the lack of stock of natural orange juice in a store located in Madrid, Spain), or becomes knowledgeable about the growing importance of vegan lifestyle (e.g., many customers ask for vegan hamburgers instead of veggie hamburgers), which has helped Mercadona to sense a new business opportunity (vegan products) ahead competitors.

Social media capability can also affect knowledge exploitation. Leveraging social media gives firms more flexibility to assimilate, apply, and leverage new/existing knowledge (knowledge exploitation). Social media facilitate the access to repositories of solutions, in which knowledge can be easily reused and recombined reducing time and effort (Grant, 1996; Jarvenpaa & Majchrzak, 2010). These repositories of knowledge allow to easily control and improve new/existing knowledge for its exploitation. For example, employees can include in corporate blogs working experience, skills, knowledge or reviews serving as a repository of new/existing knowledge, and a platform to write, link, comment other posts, making easier to interpret existing knowledge and generate new combination and interpretation of knowledge (i.e., knowledge exploitation) (Lu et al., 2015). For example, Mercadona also uses its Twitter profile to exploit new/existing knowledge. Many tweets had flooded Twitter with requests for easily finding kefir (i.e., a sour drink which contains so-called gut-friendly bacteria). Mercadona applied and leveraged this knowledge to commercialize this product in increasing demand in its stores, which has been acknowledge by their customers. For example, one customer uploaded a Kefir's picture with the following text: "If there is one thing that I like of Mercadona is that they always listen to the customers' suggestions". This example illustrates how external social media also provides "clues" on how firms can exploit new knowledge (e.g., new customer knowledge).

In summary, social media capability enables firms to acquire knowledge from customers, competitors, and suppliers. Social media capability also provides more flexibility and "knowledge exploitation clues", and enhances the firm's knowledge repository base to exploit knowledge more easily. Hence, we hypothesize that:

Hypothesis 1 (H1): There is a positive relationship between social media capability and knowledge ambidexterity.

3.2.4. Knowledge ambidexterity and innovation performance

Knowledge ambidexterity can enable innovation performance. Firms with the ability to combine simultaneously "learning-by-experimentation" (knowledge exploration) and "localized learning" (knowledge exploitation) may maximize its innovation results (Kim et al., 2012). Specifically, both knowledge exploration and knowledge exploitation can improve innovation performance. Knowledge exploration brings new knowledge to the firm increasing the diversity and heterogeneity to the firm's knowledge pool, and the possibilities of new combinations, thus improving innovation performance (Katila & Ahuja, 2002). For example, through social media, firms may obtain customer preferences, suggestions for improvement, which is critical to innovate. Moreover, exploration helps firms to better understand the market, enhancing the process of new product development (Benitez et al., 2018a). Exploration also brings to the firm a promotion of sharing and creative culture among the organization's members, potentiating radical innovation (Lubatkin et al., 2006).

Knowledge exploitation may also affect positively innovation performance. The key argument is that new discovered knowledge needs to be exploited and leveraged by the firm to create business value (Benitez et al., 2018b; Benitez et al., 2018d). Converting new knowledge in product and/or process innovations is one profitable way to create business value for the firm. In this sense, firms can identify valuable knowledge from suppliers, employees, competitors, and customers, and leverage it by performing product and process innovations (Benitez et al., 2018a; Lubatkin et al., 2006).

An illustrative example here is the case of MyStarbucksIdea. The firm Starbucks created an online platform called "MyStabucksIdea.com" to easily acquire knowledge from their customers (knowledge exploration). After that, to use, assimilate, and leverage this customer knowledge (knowledge exploitation), an expert team evaluated the best and most innovative ideas to be implemented in Starbucks. This process of exploration and exploitation of knowledge enabled this company to innovate in product and service delivery. In an initiative called "Ideas in Action" Starbucks presented the implemented product and service innovations (e.g., stevia sweetener, the new product "However-you-want-it Frappuccino"). Based on the above theoretical arguments and anecdotal evidence, we hypothesize:

Hypothesis 2 (H2): There is a positive relationship between knowledge ambidexterity and innovation performance.

3.2.5. Business value of business analytics talent: The moderator role of business analytics talent

3.2.5.1. The moderator role of business analytics talent in the relationship between social media capability and knowledge ambidexterity

We argue that when the firm has talent in business analytics, the relationship between social media capability and knowledge ambidexterity can be amplified, that is, business analytics talent can play a positive moderator role in this relationship.

Social media facilitate the exploration and exploitation of a vast amount of knowledge. However, business analytics talent is needed to have a good understanding, and to use this amount of knowledge efficiently (Chau & Xu, 2012). Firms with superior business analytics talent can collect, monitor, analyze, and summarize vast amount of unstructured new knowledge to quickly create meaningful knowledge (He et al., 2015), which can be easily stored (i.e., knowledge exploration). Firms with this capability may also extract, monitor, and analyze unstructured existing/new knowledge to be easily reused, transformed, applied, and leveraged into the firm (i.e., knowledge exploitation).

Social media data may be unstructured, subjective, and massive (Chan et al., 2016). The ideas expressed in social media can be easily misunderstood and misapplied (Faraj et al., 2011), which requires firms to use business analytics talent to effectively explore and exploit knowledge. In summary, business analytics talent is required by firms to store, assimilate, and apply the useful knowledge acquired from social media. Thus, we hypothesize that:

Hypothesis 3a (H3a): Business analytics talent positively moderates the relationship between social media capability and knowledge ambidexterity.

3.2.5.2. The moderator role of business analytics talent in the relationship between knowledge ambidexterity and innovation performance

Our organizational theory also argues that in presence of business analytics talent, the relationship between knowledge ambidexterity and innovation performance can be amplified, suggesting business analytics talent as positive moderator of this relationship. First, new knowledge elements, brought to the firm through exploration, increase the diversity and heterogeneity of the firm's knowledge pool (Katila & Ahuja 2002) increasing the possibilities of new knowledge combinations to innovate. However, this new knowledge, often derived from people with different backgrounds and expertise, can be difficult to be translated into innovative actions. This translation will be easier for talented firms in business analytics since they can obtain a quicker and deeper understanding of how effectively introduce knowledge in the innovation process through interpreting, assessing, filtering, manipulating, and leveraging this heterogeneous knowledge (Ransbotham et al., 2015).

Second, the process of innovation can be more successful when the firm determines what occurred in the past, what is occurring now, and predicts what will occur in the future (business analytics talent skills) reducing the uncertainties surrounding the innovation process (Ransbotham et al., 2015). Also, it is critical for the success of innovations to reduce the risk that new products are not accepted in the market. Firms with business analytics talent can minimize this risk by better interpreting the knowledge provided by customers and competitors (Chan et al., 2016).

Third, firms with business analytics talent that use existing knowledge are more likely to benefit from a competitive advantage in innovation because talented firms are able to link insights with business outcomes, deriving value from analytics (Ransbotham et al., 2015). Exploiting knowledge consists in using and refining new/existing knowledge, enabling the identification and recombination of valuable knowledge to improve innovation performance (Katila & Ahuja, 2002). Innovation performance may be amplified if the firm has business analytics talent, since they are able to use data mining and statistical analysis to reach a deeper understanding of the knowledge and get more transparent and accurate results to the problem recognition and resolution (Corte et al., 2017), facilitating the process of combining that knowledge to improve innovation performance. Finally, talented firms in business analytics know how to organize, standardize, and manipulate knowledge efficiently to be easily and quickly included into the innovation process. An illustrative example here is the case of Dell, which created a community called IdeaStorm to acquire customer's ideas. They used business analytic tools to monitor the bunch of data from this community, which has enabled Dell to implement more than 550 ideas, since it can see how people are using their products and the most desired (and less desired) features. As an example of one idea implemented by Dell is the backlit keyboards. One customer posted the inconvenience about finding himself many times in dark or poorly lit environments having to guess the keys, so he proposed to have a backlit keyboard. More than 3,200 customers supported this option, and more than 300 customers commented about the convenience of having a backlit keyboard on their desktops and laptops. Faced with many requests, Dell implemented backlit keyboards. Dell is considered now a world-class social media adopter for knowledge management activities (Deshpande & Norris, 2015).

In summary, business analytics talent facilitates firms the translation of heterogeneous knowledge, reducing the uncertainties surrounding the innovation process, and linking insights with business outcomes, thus amplifying the effect of knowledge ambidexterity on innovation performance. We therefore hypothesize the following:

Hypothesis 3b (H3b): Business analytics talent positively moderates the relationship between knowledge ambidexterity and innovation performance.

Figure 3.1 depicts our conceptual model graphically. Table 3.1 presents a summary of the main arguments of the proposed hypotheses.

Figure 3.1: Conceptual model (CV = Control variable)

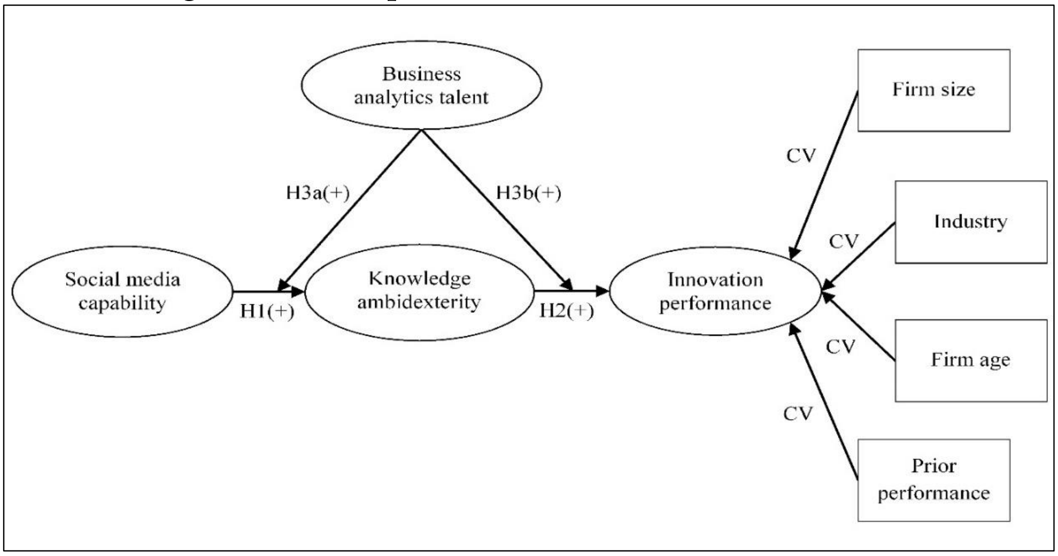


Table 3.1: Theoretical arguments summary

Hypotheses	Main theoretical arguments
H1: There is a positive relationship between social media capability and knowledge ambidexterity	Social media capability enables firms to acquire knowledge from customers, competitors, and suppliers. Social media capability also provides more flexibility and "knowledge exploitation clues", and enhances the firm's knowledge repository base to exploit knowledge more easily.
H2: There is a positive relationship between knowledge ambidexterity and innovation performance	New knowledge elements, brought to the firm through exploration, increase the diversity and heterogeneity to the firm's knowledge pool, and the possibilities of new combinations. Firms can identify valuable knowledge from suppliers, employees, competitors, and customers, and apply and leverage it performing product and process innovations.
H3a: Business analytics talent positively moderates the relationship between social media capability and knowledge ambidexterity	Firms with superior business analytics talent can collect, monitor, analyze, and summarize vast amount of unstructured new knowledge to quickly create meaningful knowledge (He et al., 2015), which can be easily stored (knowledge exploration). Firms with this capability can also extract, monitor, and analyze unstructured existing/new knowledge to be easily reused, transformed, applied, and leveraged into the firm (knowledge exploitation). For example, employing analytics to capture unstructured and massive data to know which customers have the greatest profit potential.
H3b: Business analytics talent positively moderates the relationship between knowledge ambidexterity and innovation performance	The translation of heterogeneous knowledge will be easier for talented firms in business analytics since they can obtain a quicker and deeper understanding of how effectively introduce knowledge in the innovation process through interpreting, assessing, filtering, manipulating, and leveraging this heterogeneous knowledge (Ransbotham et al., 2015). The process of innovation can be more successful when the firm determines what occurred in the past, what is occurring now, and predicts what will occur in the future (business analytics talent skills) reducing the uncertainties surrounding the innovation process (Ransbotham et al., 2015).

3.3. Research methodology

3.3.1. Sample

We tested the proposed model with a sample of the 100 small firms included in the 2013 Forbes America's Best Small Companies ranking (in short, the Forbes database). This ranking is composed by the best 100 publicly recognized U.S. small firms with sales under one billion dollars (Benitez et al., 2018a). The firms of our sample came from 30 industries: consulting (18 firms), IT (16 firms), food manufacturing (7 firms), semiconductor manufacturing (6 firms), healthcare (5 firms), chemical (5 firms), and other industries (43 firms).

Prior IS research has contextualized several types of business value of IT studies on sample of firms included in well-known rankings (as the ranking used in this study) (e.g., Benitez et al., 2018a; Benitez & Walczuch, 2012; Joshi et al., 2010), which suggests that our decision in using the Forbes database was rational. We focused on this ranking for three reasons. First, because small firms have lower portfolio of financial resources to compete more effectively in the market, leveraging their investments in social media capability and business analytics talent to innovate remains central, as compared with large firms (Benitez et al., 2018a). Second, the firms included in the Forbes database are leaders in sales and performance and then, are supposed to outperform in innovation. Third, the majority of prior IS research on social media and business activities has focused on large firms (Luo et al., 2013; Kane et al., 2014). In this sense, another distinctive feature of our research is its focus on small firms.

To check whether our sample meets the minimum required size to examine the effects included in the proposed model, prior to data collection, we performed a statistical power analysis. Assuming an anticipated medium effect size ($f^2 = 0.150$), to achieve a statistical power of 0.800, five predictors (i.e., the number of effects received by innovation performance), and an alpha of 0.05, the minimum required size for our sample was 91 (Cohen, 1988). As our sample size is 100 there is enough statistical power to estimate the proposed model.

3.3.2. Data and measures

The data used to measure the proposed model come from eight databases: Facebook, Twitter, and blog firm site, LexisNexis, Knowledge Management World, U.S. Patent and Trademark Office, Forbes, and firms' websites).

3.3.2.1. Specification of the measurement model

A clear distinction can be done between behavioral constructs and design constructs (or artifacts) (Benitez et al., 2017; Henseler, 2017). While behavioral constructs are usually modeled as common factor (reflective) models, composite-formative[8] (in short, composite) should be the preferred choice for

[8] Two types of formative measurements exist: composite-formative (artifact) and causal-formative (latent variable). The main differences between them are: (1) in composite measurement the indicators make up the construct, whereas in causal-formative measurement the indicators cause the construct, (2) high correlations among the indicators are common but not required in composite measurement, whereas correlations are not expected in causal-formative measurement, (3) the indicators of composite constructs do not involve measurement error, whereas the indicators of causal-formative constructs have measurement error, and (4) dropping an indicator alters the composite and may change its meaning, whereas dropping an indicator increases the measurement error on the causal-formative constructs (Benitez et al., 2017; Henseler, 2017).

modeling artifacts. These artifacts can be understood as theoretically justified constructions which consist of more elementary components (Benitez et al., 2018b; Benitez et al., 2018d). They are human-made objects that are typically created by executives, staff, or the firm itself, and should be modeled as a composite. The artifact serves as proxy for the concept under investigation, and can be understood as a mix of ingredients (indicators) forming the recipe (artifact) (Benitez et al., 2018b; Henseler, 2015, 2017; Rueda et al., 2017). Composite modeling is the way of estimating artifacts (Benitez et al., 2017). Based on the above arguments, all the constructs of this research were considered as artifacts and were modeled as composite. In short, in sake of brevity, we refer to artifacts as composite constructs.

3.3.2.2. Social media capability

Social media capability is a composite second-order construct composed by three dimensions: Facebook capability, Twitter capability, and blog capability (Benitez et al., 2018a; Culnan et al., 2010). We use the firm's social media activities on Facebook, Twitter, and blog because they are a good proxy to evaluate social media capability (Benitez et al., 2018a).

Facebook capability was evaluated as a composite first-order construct through number of past and future events, experience, and updates, using information from Facebook site of the firm. Experience on Facebook was measured as the average number of months that the firm has been operating in Facebook. We measured updates by scoring with 1: Low or 5: High degree of content updating in this platform, taking into account when the firm had made the last comment on Facebook: More than one month ago/in the last month/two weeks ago/in the last week/in the last two days, getting a score of 1/2/3/4/5 respectively (Benitez et al., 2018a).

Twitter capability was also operationalized as a composite first-order construct with three indicators: spent time writing tweets, experience, and updates using information collected from Twitter site of the firm and Twopcharts database. The spent time writing tweets refers to the average hours that the firm has spent writing tweets. Experience and update were measured on the same way as for Facebook capability (Benitez et al., 2018a). Following the same measure scheme mentioned above, blog capability was measured through experience and updates of the firm on blog(s) using data collected from the firm's blog(s). We measured social media capability as Benitez et al., (2018a), with data collected in 2014.

3.3.2.3. Knowledge ambidexterity

Knowledge ambidexterity is a composite first-order construct composed by two indicators: knowledge exploration and knowledge exploitation. To measure knowledge ambidexterity, we performed a structured content analysis following the Joshi et al. (2010)'s measure scheme. First, we used 18 keywords related to IT applications that support knowledge management activities to choose the firm's news published in 2013 and 2014 from LexisNexis and Knowledge Management World databases.[9] Then, these news were

[9] In measuring knowledge ambidexterity, we focused on the news published in published in 2013 and 2014 to smooth out if the firm has good or bad year (Benitez et al., 2018a; Tanriverdi, 2005).

carefully read to decide whether the firm used (or not) the specific IT applications, making distinction between those IT applications that supported the acquisition and storage of knowledge in the firm (knowledge exploration), and those IT applications that supported the application and usage of knowledge in the firm (knowledge exploitation). In that way, knowledge exploration and exploitation were measured as the total number of news on processes of knowledge management (exploration and exploitation) enabled by IT applications (Joshi et al., 2010).

3.3.2.4. Innovation performance

Innovation performance was measured using information collected from the U.S. Patent and Trademark Office database related to the period from 2007 to 2014. The process of measuring innovation performance composed two phases. In the first phase, we calculated a patent quality weighting ratio (PQWR). PQWR is the number of firm's patents published in a certain year weighted by the number of citations that these patents have received from subsequent patent within a three-year window (PQWR = Number of citations that the firm's patents of a year have received from subsequent patents within a three-year window / Number of published patents of that firm in that year). The three-year window was used to avoid vintage effects of older patents (Kleis et al., 2012). We estimated a total number of five ratios, one for each period of three years: 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014. For example, the 2011-2014 PQWR was estimated by dividing the number of citations that the firm's patents published in 2011 had received for subsequent patents within 2012-2014 by the number of firm's patents published in 2011. In this sense, we considered the number of patent citations in the period 2010-2014 to smooth out if the firm has good or bad year (Benitez et al., 2018a; Tanriverdi, 2005).

In the second phase, we created a ranking for each industry building upon these PQWR values, having for each period as many PQWR rankings as industries in our sample. Firms belonging to each industry were ranked based on their PQWR, being better positioned those firms with higher PQWR. In this way, each firm had a certain position in a specific PQWR ranking related to its industry. Based on the position of the firm in its PQWR ranking, we calculated the rate of sectoral excellence (RSE) in innovation (Benitez & Walczuch, 2012; Benitez et al., 2018b; Benitez et al., 2018d). RSE considers the position of the firm in its PQWR ranking (i.e., in its industry) related to the total number of firms on that industry. RSE was calculated as follows: RSE = 1 - (Firm's position in its industry in our PQWR ranking / Total number of firms on that industry in our PQWR ranking). The results of this calculation process were five RSEs in innovation related to 2007-2010, 2008-2011, 2009-2012, 2010-2013, and 2011-2014 for each firm. These RSEs were used as composite indicators for measuring innovation performance. Prior IS research has proven this composite is a strong measure of innovation performance (Benitez et al., 2018a).

3.3.2.5. *Business analytics talent*

Business analytics talent is a first-order construct composed by one indicator. To measure business analytics talent, we performed a structured content analysis on the firm's news published in 2013 and 2014 included in LexisNexis database.[10] Business analytics talent was measured as the natural logarithm of the total number of business analytics talent's features that were present in the firm, which provides a novel way to measure firm's business analytics talent with secondary data. First, based on the Ransbotham et al.'s (2015) research report, we selected a list of critical keywords related to business analytics talent. We identified on this report all the keywords closely related to the business analytics talent concept, resulting in a list of 22 critical keywords. Second, using these 22 keywords related to business analytics talent, we searched for the firm's news published in 2013 and 2014 included in LexisNexis database. Then, these news were carefully read to decide whether the firm had, used, or applied the specific feature of business analytics talent. Table 3.2 provides the list of these 22 keywords.

[10] Similarly as per the measures of the other variables included in the proposed model, in measuring business analytics talent, we focused on the news published in published in 2013 and 2014 to smooth out if the firm has good or bad year (Benitez et al., 2018a; Tanriverdi 2005).

Table 3.2: List of business analytics talent's key features

Construct	Reference	Keywords
Business analytics talent	Ransbotham et al. (2015)	Analytics skill(s) / analytical skill(s) Analytics technology / analytical technology Analytics insights / analytical insights Analytics talent / analytical talent Analytics training / analytical training Analytics worker(s) / analytical worker(s) / analytics Employee(s) / analytical employee(s) Analytics capability(s) / analytical capability(ies) Analytics tool(s) / analytical tool(s) Analytics expertise / analytical expertise Analytics resource(s) / analytical resource(s) Descriptive analytics Predictive analytics Prescriptive analytics Data worker(s) / data employee(s) Data engineer(s) Data science Data manager(s) Data skill(s) Data scientist(s) Talent strategy(s) Big data capability(s) Chief Analytics Officer / Chief Data Officer

3.3.2.6. Control variables

We controlled for firm size, industry, firm age, and prior performance on innovation performance. It is rational to expect that bigger and more experienced firms may have more resources to invest in innovation activities (Benitez & Walczuch, 2012; Benitez et al., 2017). Firm size was measured as the natural logarithm of the average number of employees per firm in 2013 and 2014, with data collected from Forbes database (Benitez et al., 2018a). Firm age was measured as the natural logarithm of the number of years operating of each firm in 2014 (Chen et al., 2015), with information collected from Forbes database.

Innovation performance may be dependent of the industry where the firm operates (Benitez et al., 2018a). Industry was measured as a composite first-order construct composed by 29 indicators created as follows. The sample firms were classified in 30 groups of industries determining the industry 1 as the group reference. We created 29 dummy indicators (from industry group 2 to industry group 30) for each firm (0: No, 1: Yes) with reference in industry group 1. This measurement scheme provides equidistant measures for the composite industry (Benitez et al., 2017; Benitez et al., 2018a; Henseler et al., 2016). The information needed to create this composite was collected from Forbes database and the firm website.

Prior firm performance can also influence subsequent performance (Benitez et al., 2018b). Prior performance was measured similarly to innovation performance, through a two-step process with information collected from the U.S. Patent and Trademark Office database. In the first step, we calculated the PQWR as the number of firm's patents published in any year preceding 2007 weighted by the number of citations that these patents had received from subsequent patent (PQWR = Number of citations that the firm's patents of years preceding 2007 had received from subsequent patents / Number of published patents of that firm in years preceding 2007). In the second step we ranked each firm by industry according to their PQWR values. Based on the position of the firm in its PQWR ranking, we calculated the RSE in prior innovation performance for the years preceding 2007 (Benitez et al., 2018b). The result of this process was one RSE in prior innovation performance for each firm, which was used as a single indicator for measuring prior performance.

3.4. Empirical analysis

The proposed theory was empirically tested using a PLS path modeling estimation. We employed the statistical software package Advanced Analysis for Composites (ADANCO) 2.0.1 Professional for Windows (http://www.composite-modeling.com/) (Henseler & Dijkstra, 2015). PLS is a well-developed and full-fledged structural equation modeling method of estimation (Henseler et al., 2016), which has been largely used in the field of IS (Benitez et al., 2017; Chen et al., 2015; Ringle et al., 2012), and its use is appropriate to test the proposed model for several reasons. First, PLS is appropriate for confirmatory and explanatory IS research (Benitez et al., 2017; Henseler et al., 2016; Henseler, 2018). Second, all constructs of the proposed model were specified as artifacts, and PLS is an optimal method of estimation for composite models (Benitez et al., 2017; Henseler et al., 2014; Henseler et al., 2016). Third, the proposed model has a multidimensional construct (social media capability), which increases the complexity of the model. PLS is considered a method more flexible than covariance-based method of estimations to estimate this type of models (Hair et al., 2012).

3.4.1. Measurement model evaluation

3.4.1.1.Confirmatory composite analysis

We conducted a confirmatory composite analysis to check if our structure of composite measures was correct (Benitez et al., 2017; Henseler et al., 2014). This confirmatory composite analysis analyzes the adequacy of the composite model comparing the empirical correlation matrix and the model-implied correlation matrix. We evaluated the discrepancy between the empirical correlation matrix and the saturated model-implied correlation matrix at first, and second-order levels (Benitez et al., 2017; Henseler, 2015) by calculating the standardized root mean squared residual (SRMR), unweighed least squares (ULS) discrepancy (d_{ULS}), and geodesic discrepancy (d_G) (Henseler et al., 2014). The SRMR value meet the suggested threshold of being below 0.080 (Henseler et al., 2014), and all discrepancies are below the 95%-quantile of the bootstrap discrepancies (Henseler et al., 2016) for both first and second-order steps. None of these two models should be rejected based on an alpha level of 0.05. This means that with a probability of 5% we can claim that the structure of composites of our model is correct. Table 3.3 shows the overall model fit evaluation for the confirmatory composite analysis.

Table 3.3: Results of the confirmatory composite analysis (saturated model[11])

Discrepancy	First-order level			Second-order level		
	Value	HI95	Conclusion	Value	HI95	Conclusion
SRMR	0.066	0.308	Supported	0.101	0.297	Supported
d_{ULS}	0.755	16.262	Supported	2.357	20.406	Supported
d_G	0.388	106.115	Supported	1.822	39.537	Supported

[11] "The saturated model corresponds to a model in which all constructs can freely correlate. The saturated model is useful to assess the quality of the measurement model, because potential model misfit can be entirely attributed to measurement model misspecification" (Henseler, 2017, p.183).

3.4.1.2. Evaluation of the measurement properties

The constructs of our model (social media capability, knowledge ambidexterity, innovation performance, business analytics talent) are composite, thus we evaluated their multi-collinearity, weights, loadings, and its level of significance (Benitez et al., 2017; Cenfetelli & Bassellier, 2009), by running a 4999 subsamples bootstrap analysis. To ensure that multi-collinearity is not a problem, the variance inflation factor (VIF) must be below the suggested threshold of 10 (Benitez et al., 2017; Tanriverdi & Uysal, 2015). The VIFs of the indicators/dimensions of the proposed model range from 1.112 to 6.948, suggesting that multi-collinearity is not a problem in our data (Benitez et al., 2018b). All indicators/dimensions of the model have significant weights (ranging from 0.192^{*} to 0.659^{***} for indicators, and from 0.360^{***} to 0.432^{***} for dimensions) and significant loadings (ranging from 0.569^{***} to 0.951^{***} for indicators, and from 0.841^{***} to 0.891^{***} for dimensions) except for the weight of one indicator of innovation performance (RSE 2008-2011 = 0.138). This composite indicator was retained because although its weight was not significant, its loading was (Benitez et al., 2017; Cenfetelli & Bassellier, 2009). We perform the two-step approach to estimate the proposed model since social media capability is a second-order construct. First, we freely correlated all the first-order constructs and dimensions of the second-order constructs to obtain the latent variables scores of the dimensions. Second, we used these latent variables scores as the ingredients that compose social media capability. We used the correlation weights (mode A) to estimate all constructs of our proposed model instead of the regression weights (mode B) to increase stability (Benitez et al., 2017). The measurement model evaluation is presented in Table

3.4. The results in the confirmatory composite analysis and the evaluation of the measurement properties enable us to proceed with testing the proposed hypotheses.

3.4.2. Structural model assessment

3.4.2.1. Overall model fit evaluation of the estimated model[12]

The overall goodness of the estimated model fit was also evaluated, in a similar way to the confirmatory composite analysis but for the estimated model(s) (Dijkstra & Henseler, 2015a; Henseler et al., 2014). This measure of goodness of fit evaluates the discrepancy between the empirical correlation matrix and the estimated model-implied correlation matrix (Benitez et al., 2018b; Henseler et al., 2014; Henseler, 2015). The lower the SRMR, d_{ULS}, and d_G, the better the fit between the proposed model and the data (Henseler & Dijkstra, 2015). Overall, our proposed model should not be rejected based on the alpha level of 0.05 because the SRMR value (0.047) is lower than 0.080, and all discrepancies are below the 95%-quantile of the bootstrap discrepancies (Benitez et al., 2017; Henseler et al., 2014). This means that with a probability of 5% we can claim that the proposed theory of social media and innovation is correct to explain how the corporate and IT world function.

[12] The estimated model is as specified by the analyst (Gefen et al., 2011). The difference between saturated model and estimated model lies purely in the structural model. If the estimated model is a full graph, both models will be equivalent (Henseler, 2017).

Table 3.4: Measurement properties evaluation at first- and second-order level

Construct/indicator[13]	Mean	S.D.	VIF	Weight	Loading
Social media capability					
Facebook capability: Facebook activity of the firm in terms of:			2.345	0.365***	0.865***
Number of events	5.510	18.549	1.112	0.296***	0.569***
Experience	33.773	25.582	2.126	0.449***	0.889***
Updates	2.740	2.223	2.088	0.485***	0.891***
Twitter capability: Twitter activity of the firm in terms of:			2.601	0.360***	0.891***
Spent time	17.280	32.149	1.307	0.317***	0.703***
Experience	35.752	27.651	2.114	0.448***	0.885***
Updates	2.750	2.284	2.254	0.424***	0.897***
Blog capability: Blog activity of the firm in terms of:			1.593	0.432***	0.841***
Experience	17.266	31.681	1.847	0.552***	0.918***
Updates	1.255	1.949	1.847	0.540***	0.914***
Knowledge ambidexterity					
Knowledge exploration	0.442	0.908	1.196	0.659***	0.874***
Knowledge exploitation	0.139	0.439	1.196	0.532***	0.798***
Innovation performance					
RSE 2007-2010	0.140	0.299	2.881	0.192*	0.802***
RSE 2008-2011	0.157	0.308	2.625	0.138	0.754***
RSE 2009-2012	0.143	0.299	4.577	0.266***	0.908***
RSE 2010-2013	0.122	0.278	6.948	0.252***	0.951***
RSE 2011-2014	0.167	0.309	2.966	0.297**	0.879***
Business analytics talent: Natural logarithm of the total number of analytics talent's aspects that are present in the firm	0.271	0.743			
Firm size: Natural logarithm of the total number of full-time employees	6.951	1.238			
Industry: The primary industry of the firm	0.032	0.175			
Firm age: Natural logarithm of the number of years operating the firm	3.384	0.573			
Prior performance: RSE prior years to 2007 considering patents published before 2007 weighted by the number of citations received from subsequent patents	0.269	0.354			

[13] None of the constructs/indicators was considered as the dominant in the PLS estimation.

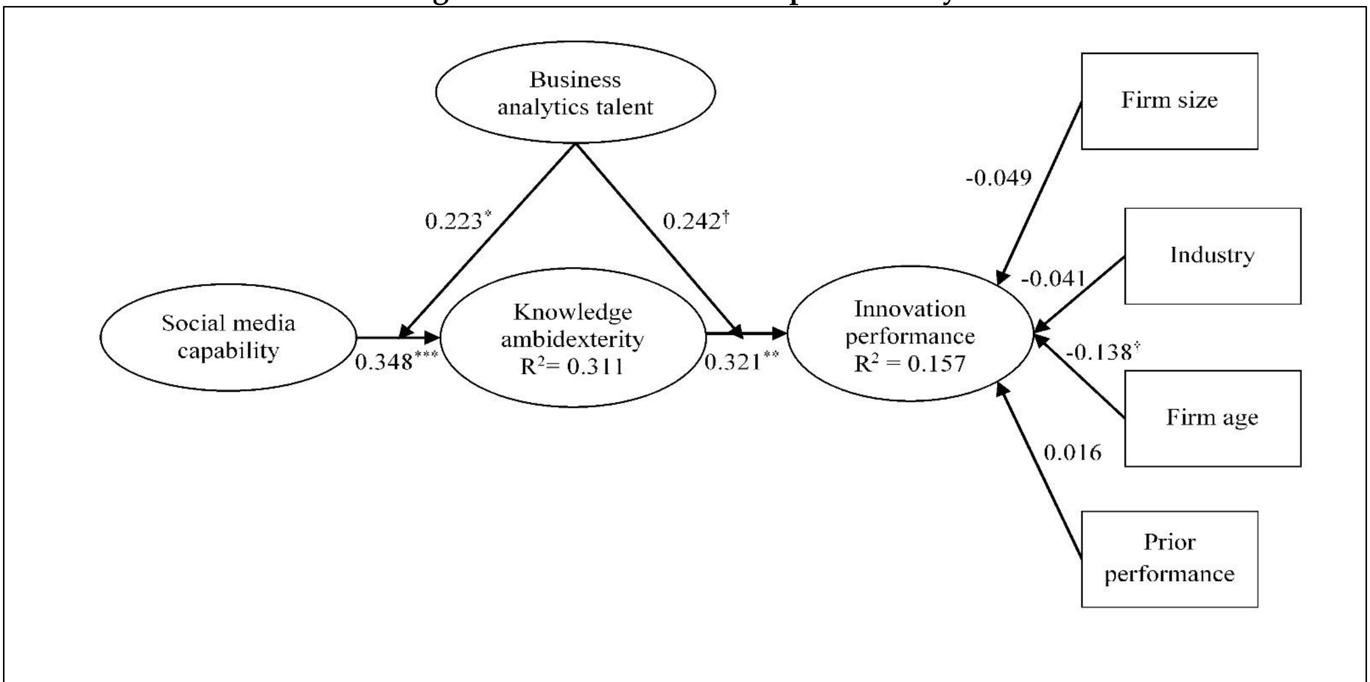
3.4.2.2. *Test of hypotheses*

To test the hypothesized relationships, we performed a PLS estimation (Dijkstra & Henseler, 2015b) by evaluating the beta coefficients and its significance of the proposed model running a bootstrap analysis with 4999 subsamples. The R^2 values and the effect size (f^2) of the proposed relationships were also evaluated. First, we evaluated a baseline model to test H1 and H2. This baseline model describes the base relationships including all control variables, and excluding business analytics talent. Second, we tested model 1 which includes business analytics talent in the baseline model, and finally, we tested model 2 which adds the interaction terms (social media capability * Business analytics talent, and knowledge ambidexterity * Business analytics talent) to the model 1 to test H3a and H3b. H1 and H2 are supported, suggesting that social media capability enables knowledge ambidexterity (H1) ($\beta = 0.441$, $p_{one\text{-}tailed} < 0.001$), and knowledge ambidexterity in turn enables innovation performance (H2) ($\beta = 0.326$, $p_{one\text{-}tailed} < 0.01$). H3a is also supported, which suggests that the relationship between social media capability and knowledge ambidexterity is amplified when firm has business analytics talent ($\beta = 0.223$, $p_{one\text{-}tailed} < 0.05$). Finally, we also find some support for H3b, which suggests that business analytics talent amplifies in some extent the relationship between knowledge ambidexterity and innovation performance ($\beta = 0.242$, $p_{one\text{-}tailed} < 0.10$).[14] Thus, business analytics talent plays a moderator role in these

[14] If prior performance is removed from the proposed model, the coefficient implied in H3b is 0.259 significant at 0.05 level in the model 2 with direct effects. After careful consideration, we decided to keep prior performance as control variable because this decision provides a more rigorous empirical analysis (Benitez et al., 2018b).

relationships.[15] Control variables did not show any significant relationship with innovation performance in the context of our model. The R^2 values are 0.195 and 0.127 for baseline model, 0.282 and 0.137 for model 1, and 0.311 and 0.157 for model 2. The f^2 values of the key relationships of the proposed model range from 0.114 to 0.242 for baseline model, from 0.126 to 0.141 for model 1, and from 0.024 to 0.156 for model 2, which indicate from weak to medium-large effect sizes between the exogenous and endogenous variables of the proposed theory (Benitez et al., 2017; Cohen, 1988). Table 3.5 shows the results of the test of hypotheses. Table 3.6 presents the correlation matrix.

Figure 3.2: Results of the empirical analysis



[15] Knowledge ambidexterity can also be operationalized as the natural logarithm of the result of multiplying the total number of news supporting exploration and the total number of news supporting exploitation (He & Wong, 2004). The analysis yields similar results, providing an H2 beta coefficient of 0.287*, and an H3b beta coefficient of 0.286*.

Table 3.5: Results of the test of hypotheses

Beta coefficient	Baseline model	Mediation baseline model	Model 1	Mediation model[16] 1	Model 2	Mediation model 2
Social media capability → Knowledge ambidexterity (H1)	0.441*** (6.947) [0.310, 0.562]	0.441*** (6.947) [0.310, 0.562]	0.337*** (4.821) [0.190, 0.465]	0.337*** (4.821) [0.189, 0.465]	0.348*** (5.116) [0.221, 0.485]	0.348*** (5.116) [0.221, 0.485]
Knowledge ambidexterity → Innovation performance (H2)	0.326** (2.605) [0.063, 0.553]	0.279* (1.995) [-0.012, 0.538]	0.372** (2.825) [0.102, 0.619]	0.326* (2.263) [0.027, 0.595]	0.321** (2.609) [0.094, 0.575]	0.266* (1.989) [0.003, 0.541]
Social media capability * Business analytics talent → Knowledge ambidexterity (H3a)					0.223* (1.903) [0.058, 0.510]	0.223* (1.903) [0.058, 0.510]
Knowledge ambidexterity * Business analytics talent → Innovation performance (H3b)					0.242† (1.427) [-0.133, 0.533]	0.259† (1.534) [-0.109, 0.552]
Social media capability → Innovation performance		0.119 (0.995) [-0.112, 0.357]		0.139 (1.155) [-0.104, 0.370]		0.153 (1.252) [-0.095, 0.386]
Business analytics talent → Knowledge ambidexterity			0.313*** (3.630) [0.158, 0.498]	0.313*** (3.630) [0.158, 0.498]	0.168* (1.965) [-0.034, 0.300]	0.168* (1.965) [-0.034, 0.300]
Business analytics talent → Innovation performance			-0.113 (-0.892) [-0.351, 0.135]	-0.134 (-1.077) [-0.363, 0.117]	-0.285* (-2.132) [-0.520, -0.013]	-0.320** (-2.447) [-0.537, -0.043]
Firm size → Innovation performance (control variable)	-0.038 (-0.467) [-0.203, 0.122]	-0.047 (-0.579) [-0.207, 0.108]	-0.044 (-0.563) [-0.203, 0.101]	-0.055 (-0.710) [-0.213, 0.092]	-0.049 (-0.635) [-0.206, 0.097]	-0.062 (-0.797) [-0.217, 0.088]

[16] Mediation model refers to the model with direct effects.

Beta coefficient	Baseline model	Mediation baseline model	Model 1	Mediation model[16] 1	Model 2	Mediation model 2
Industry → Innovation performance (control variable)	-0.021 (-0.167) [-0.252, 0.244]	-0.012 (-0.097) [-0.252, 0.251]	-0.031 (-0.240) [-0.276, 0.238]	-0.023 (-0.174) [-0.271, 0.240]	-0.041 (-0.316) [-0.286, 0.232]	-0.033 (-0.250) [-0.279, 0.231]
Firm age → Innovation performance (control variable)	-0.105 (-1.016) [-0.305, 0.092]	-0.047 (-0.755) [-0.289, 0.125]	-0.119 (-1.120) [-0.328, 0.082]	-0.092 (-0.858) [-0.305, 0.112]	-0.138† (-1.303) [-0.346, 0.066]	-0.111 (-1.031) [-0.322, 0.095]
Prior performance → Innovation performance (control variable)	-0.017 (-0.156) [-0.230, 0.188]	-0.030 (-0.272) [-0.243, 0.179]	-0.005 (-0.043) [-0.220, 0.208]	-0.018 (-0.158) [-0.234, 0.206]	0.016 (0.146) [-0.205, 0.228]	0.004 (0.033) [-0.215, 0.223]
R^2 / Adjusted R^2						
Knowledge ambidexterity	0.195 / 0.186	0.195 / 0.186	0.282 / 0.267	0.282 / 0.267	0.311 / 0.290	0.311 / 0.290
Innovation performance	0.127 / 0.080	0.137 / 0.082	0.137 / 0.081	0.151 / 0.086	0.157 / 0.093	0.174 / 0.102
Discrepancy						
SRMR value	0.030	0.025	0.028	0.021	0.047	0.045
SRMR HI_{95}	0.054	0.049	0.043	0.039	0.099	0.098
d_{ULS} value	0.026	0.017	0.027	0.016	0.171	0.159
d_{ULS} HI_{95}	0.081	0.068	0.068	0.055	0.756	0.750
d_G value	0.007	0.005	0.008	0.005	0.131	0.126
d_G HI_{95}	0.021	0.017	0.021	0.016	0.462	0.456
f^2						
Social media capability → Knowledge ambidexterity	0.242	0.242	0.141	0.141	0.156	0.156
Knowledge ambidexterity → Innovation performance	0.114	0.071	0.126	0.088	0.087	0.054
Social media capability * Business analytics talent → Knowledge ambidexterity					0.043	0.043

Beta coefficient	Baseline model	Mediation baseline model	Model 1	Mediation model[16] 1	Model 2	Mediation model 2
Knowledge ambidexterity * Business analytics talent → Innovation performance					0.024	0.028
Social media capability → Innovation performance		0.012		0.017		0.021
Business analytics talent → Knowledge ambidexterity			0.122	0.122	0.022	0.022
Business analytics talent → Innovation performance			0.012	0.016	0.035	0.045
Firm size → Innovation performance (control variable)	0.001	0.002	0.002	0.003	0.002	0.004
Industry → Innovation performance (control variable)	0.000	0.000	0.001	0.000	0.001	0.001
Firm age → Innovation performance (control variable)	0.008	0.005	0.011	0.006	0.015	0.009
Prior performance → Innovation performance (control variable)	0.000	0.001	0.000	0.000	0.000	0.000

Note: t-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square bracket (based on n = 4999 subsamples). $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on t(4998), one-tailed test].

Table 3.6: Correlation matrix

	1	1.1	1.2	1.3	2	3	4	5	6	7	8
1. Social media capability	1.000										
1.1. Facebook capability	0.865	1.000									
1.2. Twitter capability	0.891	0.750	1.000								
1.3. Blog capability	0.841	0.533	0.596	1.000							
2. Knowledge ambidexterity	0.441	0.358	0.354	0.423	1.000						
3. Innovation performance	0.253	0.243	0.203	0.212	0.339	1.000					
4. Business analytics talent	0.332	0.281	0.256	0.318	0.425	0.066	1.000				
5. Firm size	0.050	0.062	0.071	0.004	0.096	-0.026	-0.044	1.000			
6. Industry	0.077	0.025	0.041	0.123	0.095	0.074	0.052	-0.274	1.000		
7. Firm age	-0.236	-0.212	-0.181	-0.216	-0.185	-0.162	-0.180	0.278	-0.545	1.000	
8. Prior performance	0.129	0.135	0.127	0.079	0.062	0.022	0.142	-0.225	0.198	-0.136	1.000

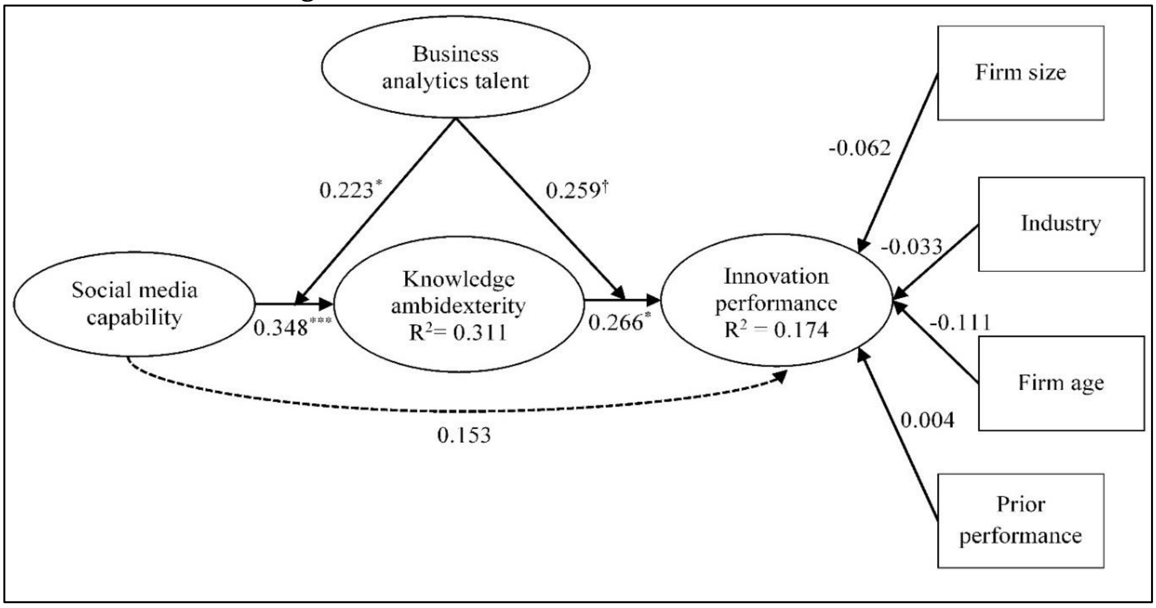
3.4.3. *Mediation analysis*

Based on the Zhao et al.'s (2010) approach for mediation analysis, we performed two mediation analyses to evaluate the indirect effects involved in the proposed model, and thus analyzing the mediation role of knowledge ambidexterity in the relationship between social media capability and innovation performance. To do that, we added a link from social media capability to innovation performance in (1) our baseline model (mediation baseline model), and (2) model 2 (mediation model 2). The models with direct effects are not better models to be considered in the test of hypotheses because the models without direct effects do not have significantly worse fit than the models with direct effects [i.e., the models without direct effects fitted with the same probability (5% for all discrepancies) than mediation models (Benitez et al., 2017; Benitez et al., 2018b). We evaluated the indirect effects of both mediation models (0.123* and 0.093* respectively), which are significant at 0.05 level, while the direct effects are not (0.119 and 0.153 respectively) suggesting that the existence of a full mediation (Benitez et al., 2017; Zhao et al., 2010). Thus, the effect of social media capability on innovation performance through knowledge ambidexterity is significant, suggesting that knowledge ambidexterity plays a mediator role in the relationship between social media capability and innovation performance. In these mediation models the rest of hypotheses (H1, H2, H3a, and H3b) remain supported, strengthening the results of the test of hypotheses. Table 3.7 presents the values of indirect, direct, and total effects. Figure 3.3 presents the path coefficients obtained in the model with direct effects.

Table 3.7: Mediation analysis: Indirect, direct, and total effects[17]

Model	Relationship	Indirect effect	Direct effect	Total effect
Baseline model	Social media capability → Innovation performance	0.123* (1.895) [-0.006, 0.254]	0.119 (0.995) [-0.112, 0.357]	0.242* (2.162) [0.011, 0.450]
Model 2	Social media capability → Innovation performance	0.093* (1.869) [0.001, 0.199]	0.153 (1.252) [-0.095, 0.386]	0.245* (2.118) [0.012, 0.465]

Figure 3.3: Results of the mediation model 2



[17] The total effect(s) is(are) the sum of the indirect effect(s) plus the direct effect(s).

3.5. Discussion and conclusions

3.5.1. Implications and key contributions to IS research

Managing organizational knowledge is critical in increasingly competitive environments (He et al., 2015). Prior IS literature has considered social media as a key source of information and data (Leonardi, 2014). However, acquiring and generating social media data is not a sufficient condition to create business value. Monitoring, analyzing, and identifying relevant information is key in transforming social media data into business gains (Ransbotham et al., 2015). Firms find difficult to efficiently select and assimilate social media data and convert them into innovation outcomes (Chan et al., 2016). Trying to shed some light on this contemporary research problem, we argue that the effective application of social media data into innovations will be achieved if firms are ambidextrous, and have business analytics talent. The aim of this study was to analyze the impact of social media capability on knowledge ambidexterity and innovation performance, and the potential moderator role of business analytics talent on this equation. We provided an organizational theory on social media and innovation emphasizing on two key organizational agents in the equation: knowledge ambidexterity and business analytics talent. The proposed theory was tested on a sample of U.S. firms. The empirical analysis provides a strong support to our theory.

How does social media capability influence innovation performance? The results of the empirical analysis show that social media capability facilitates the firm to be knowledge ambidextrous (firm’s proficiency in exploring new knowledge and exploiting existing/new knowledge) as social media are new organizational channels that facilitate knowledge management (e.g., acquire and transfer new knowledge, and recombine, modify, and integrate new/existing knowledge). That is, social media capability facilitates firms to acquire knowledge from customers, competitors, employees, and suppliers, and provides more flexibility and improving the firm's knowledge repository to exploit knowledge more easily. This knowledge ambidexterity facilitates firms to achieve greater innovation performance because exploring new knowledge increases diversity and heterogeneity to the firm's knowledge pool, and using and refining new/existing knowledge help the firm to understand knowledge and facilitates the identification of valuable knowledge. In that way, firms can identify valuable knowledge from suppliers, employees, competitors, and customers, and apply and leverage this useful knowledge to innovate more and better. Business analytics talent amplifies the impact of social media capability on knowledge ambidexterity, and the impact of knowledge ambidexterity on innovation performance because business analytics talent helps the firm to quickly create meaningful knowledge from unstructured new knowledge, and to better interpret the knowledge diminishing uncertainties surrounding innovation. In this sense, the empirical analysis extensively supports our organizational theory.

This study provides an organizational theory of social media and innovation that has several contributions to the field of IS. First, the business value of social media in fostering firms' innovation was not clear in prior IS research, thus there was a recognized necessity to study the organizational use of social media for supporting firm's innovation activities (Chan et al., 2016; Dong & Wu, 2015). Benitez et al., (2018a) examine the *complementary role* of social media in the impact of IT infrastructure on innovation. In a different way, we focused on the *enabling role* of social media in innovation activities. Specifically, we develop the concept of social media capability, explains theoretically, and shows empirical evidence on how firms can create business value from social media capability by improving innovation performance. The focus of our theoretical lens to explain the impact of social media capability on innovation performance was knowledge ambidexterity. This is the first primary contribution of this manuscript.

Second, drawn from the Ransbotham et al. (2015) (a managerial paper), this study develops the concept and measures of business analytics talent, and shows how this capability positively moderates the relationships between social media capability and knowledge ambidexterity, and between knowledge ambidexterity and innovation performance. This study suggests that business analytics talent is a complementary capability of social media capability and knowledge ambidexterity, since they mutually reinforce in such a way that the presence of business analytics talent increases the value of social media capability on knowledge ambidexterity, and the value of knowledge ambidexterity on innovation performance. Thus, business analytics talent helps firms to create business value from social media capability, and knowledge ambidexterity. To the best of our knowledge, this is a unique theoretical contribution for the IS research.

3.5.2. Limitations and future directions for IS research

This research has also some limitations. First, these results can be only generalized to small firms in the U.S. market. Future IS research may investigate whether our proposed theory is also supported on different geographic markets. Second, we considered a limited number of social media platforms. Although we examined three of the most popular external social media platforms, our research does not explore enterprise social media platforms (e.g., Microsoft Yammer) and other emerging external social media platforms (e.g., LinkedIn). Further IS research can extend this organizational theory by examining enterprise social media platforms and other new external social media platforms. The development of social media capability and its exploitation to create business value may be contingent to the social media governance mechanisms implemented by the firm. Future IS research should theorize and empirically examine the effects of social media governance mechanisms on the business value of social media technologies.

3.5.3. Implications for managers

The findings of this study also provide important implications for managers. First, developing social media capability helps firms to become knowledge ambidextrous to finally achieve innovation performance. Therefore, managers should be aware of the benefits associated with the usage of social media to acquire customer, competitor, employee, and supplier data, and communicate their products and initiatives to collect valuable opinions, preferences, suggestions for improvement, and ideas from customers, employees, and suppliers. As illustrated above in IdeaStorm, Dell provides a platform to build interactive relationships with their customers and makes them participants of the improvement of existing products and creation of new ones, helping firm to co-create business value. Moreover, firms which often communicate their products on social media explore and exploit social knowledge to innovate better and more, as it has been suggested in the MyStarbucksIdea example. Social media have come to stay for business activities. Thus, managers should invest, deploy, and leverage social media to acquire and share knowledge for innovation.

Second, firms can amplify the impact of social media capability on knowledge ambidexterity, and the impact of knowledge ambidexterity on innovation performance if they recruit, develop, and retain business analytics talent. Managers should be aware of the importance of having business analytics specialized staff, keeping in mind the expected shortage of this talent in the market. Thus, managers should make extra efforts in attracting and retaining business analytics specialized people (e.g., developing employer branding), and mostly training those people which display high potential. Business analytics talented firms can benefit from social media and knowledge ambidexterity at a higher level, since social media capability and business analytics talent reinforce each other to obtain better knowledge ambidexterity. Knowledge ambidexterity and business analytics talent reinforces each other to create greater innovation gains. These lessons learned are very relevant for IT and business executives, and analysts.

3.5.4. Concluding remarks

Innovation is one of the competitive priorities for the contemporary firm. Social media are one of the technology resources to transform digitally the company, build a powerful business strategy, and survive in the long run in the digital disruption era. This manuscript proposes an organizational theory of social media and innovation that emphasizes the roles of knowledge ambidexterity and business analytics talent. We found that social media capability enables firms to achieve effectively exploration and exploitation of knowledge, which in turn increases innovation performance. In addition, business analytics talent reinforced these relationships. By drawing on the lens of knowledge ambidexterity and business analytics talent, we provide to the IS research community with a postulated theory on business value of IT (social media) for innovation. Of course, IT does matter.

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4

IMPACT OF SOCIAL MEDIA-DRIVEN CUSTOMER ENGAGEMENT ON MOVIE PERFORMANCE

4. IMPACT OF SOCIAL MEDIA-DRIVEN CUSTOMER ENGAGEMENT ON MOVIE PERFORMANCE

Abstract

This study examines the impact of customer engagement via social media, specifically personal and interactive engagement, on movie performance (i.e., opening-weekend box office revenue), and the impact of the interaction of both customer engagements on movie performance on a sample composed of 966 movies. The empirical analysis suggests that personal and interactive engagement influence movie performance, and that the positive effect of personal and interactive engagement on performance are mutually reinforcing.

4.1. Introduction

For the past decade, a plethora of social media applications such as blogs, photo-sharing platforms, social gaming, microblogs, chat apps and social networks have experienced a rapid proliferation. The phenomenal growth mirrors that the number of worldwide users is expected to reach 2.95 billion by 2020, which entails around a third of the Earth's entire population (Statista, 2018). Social media, which is interactive in nature, enables to establish conversations between customers and firms, involving customers in content generation and value creation, and building enduring relational exchanges with strong emotional bonds with their customers through social media (Sashi, 2012). In essence, social media has profoundly changed the word-of-mouth (WOM) landscape, transforming the target from one or a few friends into the entire world (Duan et al., 2008). For example, a social media campaign, run for Make-A-Wish Foundation and Walt Disney Park under the hashtag #ShareYourEars, asked the audience to post a picture of them with the Mickey Mouse Ears, and for every such post Disney Park donated $5 to Make-A-Wish. The WOM generated via social media was immense doubling the original amount that Disney initially planned on donating and getting a tremendously high user-engagement (Walt Disney Park, 2017). WOM is a behavioral expression of customers which represent a manifestation of customer engagement (Van Doorn et al., 2010). In addition, WOM via social media (i.e., a special case of online WOM) is a dominant channel for raising customer awareness in which users implicitly/explicitly communicate their opinions and belief (Oh et al., 2017) and for gaining more profit. This particular phenomenon has piqued increasing interest, as Giamanco and Gregoire (2012) pointed out that *"with a little managerial discipline, all that clicking, following, and sharing will win more business"*.

Recognizing the importance of social media in creating WOM vis-à-vis entertainment such as movies is key because, as a cultural artifact, movies tend to attract great public interest, and therefore, communication among users about movies can be expected to exist (Liu, 2006) in social media platforms such as Facebook, Twitter, or YouTube. The increasing importance of customer engagement via social media in sales has encouraged academics to study its role, its main benefits and challenges, and the role that practitioners play in using this additional information to forecast future sales and to develop effective targeting strategies for increasing performance.

A mix of studies represents this emerging body of research in IS. Previous studies have analyzed the relationship between social media customer engagement and economic performance in the movie industry. Our research differs from previous customer engagement studies in several important ways. First, most research in the literature has focused on review-type of WOM (e.g., Duan et al., 2013; Eliashberg & Shugan, 1997; Liu, 2006). Departing from those studies, we focused on Facebook, Twitter, and YouTube where social structural information is available, thus enabling to determine how content is disseminated (Rui et al., 2013). Different from customer reviews, the effect of online WOM is likely to be more consistent with social media data because social media is a push-based communication platform (i.e., the awareness effect affects user's behavior only by giving information) instead of a pull-based communication platform (i.e., the persuasive effect affects user's behavior by altering user's preferences toward the movie and thus influencing their decision) (Rui et al., 2013; Yoon et al., 2017).

Second, we consider data from multiple social media channels. Previous studies such as Rui et al. (2013) have leveraged social media to analyze customer engagement on economic performance. However, most of these studies, in the same way as those focusing on review-type WOM, consider just one single channel.

Third, we focus on pre-consumption WOM. Most previous research have focused on post-consumption WOM (e.g., Duan et al., 2008) especially those who used data from customer reviews. Also, research which used data from social media consider the customer engagement after the release of a movie, focusing on post-consumption patterns (e.g., Yoon et al., 2017). Rui et al. (2013) have disentangled the post-consumption and pre-consumption WOM, however, this pre-consumption WOM is affected by post-consumption WOM since those users who have not watched the movie yet may access information and opinions from users who have already watched the movie. To avoid that, we consider the customer engagement occurred before the release of the movie. Gopinath et al. (2013) consider the pre-consumption activities on blogs, but in analyzing them, they only use one single channel (i.e., blogs). Moreover, they consider blog volume and blog valence, but they do not consider the interaction of users with the blogs (e.g., comments on blogs, number of readers…), focusing just on interactive engagement of the blogger. Also, this study considers the opening day, whereas we select opening weekend. We select opening weekend because Saturday and Sunday usually are non-working days, which it is rational to think people spend more leisure time (e.g., going to the movies) in these days than just on Friday.

In the literature, only one study (Oh et al., 2017) examines the effectiveness of customer engagement on economic performance by focusing on multiple social media channels in the movie industry and pre-purchase consumption. Although Oh et al. (2017) explores the relationships between personal engagement (i.e., intrinsically motivated which involves the search of stimulation and inspiration through the engagement with the content) and interactive engagement (i.e., intrinsically and extrinsically motivated which involves socializing and participating with the community through the engagement with the content and the users) on economic performance considering multiple channels, they did not analyze the complementary role of these two types of engagement. Their study, in the same way as previous ones analyzing the effectiveness of customer engagement on economic performance in movie industry, focuses on U.S. market (e.g., Duan et al., 2013; Gopinath et al., 2013; Yoon et al., 2017). However, it is well-known that other markets are excelling as movie producers and frequent movie viewers such as the United Kingdom (UK), mainly due to the massive boost from the government (e.g., reducing taxes) and Spain (Anand, 2017; Kiprop, 2018). This investigation examines the effectiveness of personal engagement and interactive engagement on economic performance on UK and Spanish markets. Moreover, as we have limited understanding of how they interact to affect movie performance (i.e., opening-weekend box office revenue), we study the complementary role of both customer engagement in affecting revenue.

In response, the current study seeks to address the following questions: (1) Can customer engagement via social media predict and influence future movie performance? And (2) How does personal engagement interact with interactive engagement to impact on future movie performance? This study aims to examine the potential role that customer engagement via social media plays in predicting and influencing the movie performance. This investigation thus examines the impact of customer engagement via social media, specifically personal engagement and interactive engagement, on movie performance, and the impact of the interaction of both customer engagements on movie performance. This research theorizes that personal engagement and interactive engagement influence movie performance, and that the positive effect of personal and interactive engagement on performance are mutually reinforcing. In doing that, we test our theory using partial least squares (PLS) path modeling with a secondary dataset on a sample of 966 movies.

The remainder of this paper is organized as follows. Next, we discuss the literature review that informs this work. The third section explains the theory on which the proposed model is based and develops the hypotheses. The forth section explains the research context of this study. The fifth and sixth sections present the research methodology, empirical analysis and results. Subsequently, the paper concludes with a discussion of the findings and implications of the study.

4.2. Theoretical background and research model

Customer engagement is gaining mounting attention of academics and practitioners due to its critical role in the success of the firms (Sashi, 2012), and its related benefits such as customer satisfaction (Brodie et al., 2013), the tendency of reputation to spread by WOM (Cheung et al., 2011; Oh et al., 2017), firm performance and firm reputation (Van Doorn et al., 2010). Previous studies have conceptualized engagement as consequences of engagement rather than engagement itself (Calder et al., 2009). What constitutes engagement? The answer to this question is unclear since there is no agreement on the optimal way to conceptualize engagement (Dessart et al., 2016). Moreover, the expression of engagement dimensions may vary across context. For example, with regard to Gambetti et al. (2012), customer engagement comprises cognitive aspects (i.e., experience), emotional aspects (i.e., feeling), behavioral aspects (i.e., participation), and social aspects (i.e., the interaction and sharing of experiences and content. Calder et al. (2009) specify eight online engagement dimensions. To model customer engagement accurately, the concept of customer engagement behavior has been proposed (Oh et al., 2017; Van Doorn et al., 2010). Customer engagement behavior refers to behavioral manifestations from customers toward a firm or a brand, beyond purchase, resulting from motivational drivers. The behavioral focus of customer engagement behavior is an appropriate proxy for customer engagement, thus we use customer engagement behavior as a meaningful representation of the customer engagement via social media (Oh et al., 2017; Van Doorn et al., 2010). WOM is an example of customers' behavioral expression which represent a manifestation of customer engagement (Van Doorn et al., 2010). WOM is thought to be a more credible and trustworthy source, which is more readily accessible through social networks (Liu, 2006) such as social media. Unsurprisingly, online experience is thought to be more interactive, more social, more participatory, and so forth (Calder et al., 2009), thus it is important to fully understand the customer engagement in the context of online platforms (Table 4.1).

Table 4.1. Previous customer engagement conceptualization

Author(s)	Source	Customer engagement conceptualization
Gambetti et al. (2012)	International Journal of Marketing Research	Customer engagement comprises cognitive aspects, emotional aspects, behavioral aspects, and social aspects.
Calder et al. (2009)	Journal of Interactive Marketing	Personal engagement, and interactive engagement.

Online customer engagement attracts significant and growing attention from academics and practitioners (Dessart et al., 2016). Customer can engage concurrently with actors as communication medium (Calder et al., 2009). Engagement can be conceptualized as the collection of the motivational experiences customers have with the site (Pagani & Mirabello, 2011). Many classifications have been considered to conceptualize customer engagement. We follow the classification of Calder et al., 2009 which distinguish between personal engagement and interactive engagement. Personal engagement, which is intrinsically motivated, involves the search of stimulation and inspiration through the engagement with the content. The personal engagement affirms their self-esteem and produce intrinsic enjoyment to them, being influenced by individual user qualities. With personal engagement, users use the site to make easier their interactions with other people in order to get useful information and valuable input from other users (Calder et al., 2009). Interactive engagement, which is intrinsically and extrinsically motivated, involves socializing and participating with the community (Calder et al., 2009; Oh et al., 2017) through the engagement with the content and the users, which also produce utilitarian worth, and intrinsic enjoyment to them. With interactive engagement, users get valuable input from the community of users by participating and socializing on the site. Interactive engagement is influenced by the social relevance rather than the individual qualities of the user, suggesting a larger engagement experience (Calder et al., 2009). Personal and interactive engagement have been found to affect reactions to the advertising effectiveness (Calder et al., 2009). Also, both types of engagement (i.e., personal, and interactive engagement) have been found to differentially influence both active and passive behavior (Pagani & Mirabello, 2011). Meanwhile, Pagani and Malacarne (2017) suggests that personal engagement influences active usage when users have more privacy concerns, and interactive engagement affect passive usage (i.e., the more people experience a deep sense of community the more they are interested in reading other comments or collecting information). In general, it is believed that WOM affects users' movie selection, being attributable to WOM the success of several movies such as *Star Wars: Episode 1 – The Phantom Menace* (Liu, 2006).

Previous studies have analyzed the relationship between social media customer engagement and economic performance in the movie industry. Duan et al. (2008) suggest that both a movie's box office revenue and WOM valence affect WOM volume, which in turn affects box office performance. Furthermore, Rui et al. (2013) find that Twitter WOM affects movie sales, and this effect is larger in WOM from users with more Twitter followers. Also, they find that positive and negative Twitter WOM are associated with higher and lower movie sale, respectively. Gopinath et al. (2013) suggest that release day performance is more affected by prerelease blog volume and advertising, whereas postrelease performance is affected by postrelease blog valence and advertising. This study seeks to understand geographical differences across different markets. Liu (2006) suggests that WOM activities are the most active during a movie's prerealese and opening week, and WOM information offers explanatory power for box office revenue.

4.3. Theory and hypotheses

To examine the impact of WOM via social media, we adopt the prospect theory, a well-known decision process theory (Tversky & Kahneman, 1981). This theory explains that individuals evaluate more severe the losses than the gains of the same amount of utility (Yoon et al., 2017). Similar to Yoon et al., 2017, we considered a gain if customers receive more activity on social media, and a loss if customer receive less activity on social media. Moreover, it was assumed that customers would choose to watch a movie which receive higher activity in social media because it is valued as higher quality movie, and customers are less likely to choose a movie which receive less activity in social media because it is value as lower quality movie. Thus, the level of activity on social media for a movie influences the effect of WOM via social media.

We draw on customer engagement behavior perspective to analyze how customer engagement behavior influences economic performance. Customer engagement behavior captures how customers behave exhibiting the relation with a particular product, and it is an appropriate proxy for customers' level of engagement. Thus, it can be used to predict the effects of this customer engagement on the firm's economic performance (Oh et al., 2017; Van Doorn et al., 2010).

The theoretical framework of complementary resource perspective states that complementarity among firm's resources explains variations in firm performance. Two resources/capabilities will be complementary when the effect of working together is superior than the effect of these resources/capabilities working in isolation (Ennen & Richter, 2010). Based on this theory, we propose that personal engagement and interactive engagement complement each other (i.e., mutually reinforcement) to amplify the effect on movie performance.

4.3.1. Personal engagement and movie performance

Personal engagement involves the search of stimulation and inspiration through the engagement with the content, which affirms their self-esteem and produce intrinsic enjoyment to them. With personal engagement, users use the site to make it easier for their interactions with other people in order to get useful information and valuable input from other users. Personal engagement is influenced by individual qualities of the user, and it is intrinsically motivated (Calder et al., 2009).

As discussed previously, WOM is a behavioral expression of customers and represents a manifestation of customer engagement (Van Doorn et al., 2010). WOM volume is related to awareness effect since a higher WOM volume will influence the probability that a customer hears about the movie and thus the probability to generate higher sales (Liu, 2006). In addition, sales will likely occur in the first weekend because movies are in the theaters only for limited time, and the customers do not have enough time to act on the desire to go to watch them (Liu, 2006).

Movies are likely to cause active prerelease WOM because they are intangible and experiential cultural goods (Liu, 2006). Most WOM in social media comes from other moviegoers that may reflect popularity and it is perceived as a more trustworthy source of information (Liu, 2006). Also, a lack of information and experience about the movie before releasing makes the customers to be more likely to accept online WOM (Brodie et al., 2013).

Moreover, social media sites such as Facebook, Twitter, and YouTube enable engagement with the content (i.e., personal engagement) through reading movie news, liking pages and content, following and subscribing to movie channels, watching movie trailers, and so on. These actions serve as stimulation and inspiration through the consumption of content which may be inspirational for the users. Users may associate themselves with the movie impacting positively on their personal self-esteem and self-worth. Also, users may experiment intrinsic enjoyment by watching movie trailers, and utilitarian value by receiving future content sent by the movie (Oh et al., 2017). A representative example is that Facebook users spend up to five times as much money on products which they like on Facebook than users who do not like that product on Facebook (Hollis, 2011; Oh et al., 2017).

Social media can be considered a WOM platform to accelerate the exchange of information among users and to reduce information asymmetries between buyers and sellers, making the selling process more efficient (Guesalaga, 2016). It is more likely that users know well the movie and thus choose the movie, increasing the movie performance of the firm. Active and official movie social media profile is perceived as if the firm is eager to build a relationship with customers, thus customer become more willing to watch the movie (Wang & Kim, 2017). It has been found that intention tweets may increase the movie performance by $157,905 for an increase of one percent in intention tweets, suggesting that the preconsumption WOM has a significant amount of credibility (Rui et al., 2013). Hence, it is rational to hypothesize that:

H1. There is a positive relationship between personal engagement and movie performance

4.3.2. Interactive engagement and movie performance

Interactive engagement involves socializing and participating with the community (Calder et al., 2009; Oh et al., 2017) through the engagement with the content and the users, which also produce utilitarian worth and intrinsic enjoyment. With interactive engagement, users get valuable input from the community of users by participating and socializing on the site. Interactive engagement is influenced by the social relevance rather than the individual qualities of the user, and it is intrinsically and extrinsically motivated, suggesting a larger engagement experience (Calder et al., 2009).

Social media sites such as Facebook, Twitter, and YouTube enable engaging with the content and users (i.e., interactive engagement) through participation, discussion and content sharing with others by sharing movie trailers, writing comments about movies, sharing content about movies, and receiving feedback from others (Oh et al., 2017).

Firms using the interactive features of social media create brand image, better users experience, and more purchasing behaviors (Wang & Kim, 2017). More talk about a movie is associated with higher sales (Rui et al., 2013). Interactive engagement increases knowledge and familiarity about the movie and can increase the intention to watch it (i.e., purchase intention) (Oh et al., 2017). Also, users trust and value the opinions from peers when discussing brand endorsed by them (Kozinets et al., 2010; Oh et al., 2017), knowing that a peer-to-peer environment provides more candid referrals and warnings (Giamanco & Gregorie, 2012).

Social media can maintain an interactive relationship between users and firms, building an enduring relational exchange (Sashi, 2012; Wang & Kim, 2017). Engaged customers become advocates for the movie in interactions with other users on their social media sites, turning themselves into fans. These fans tend to be more loyal and committed to the movie (Wang & Kim, 2017), and thus are more open to watching the movie. We thus hypothesize the following relationship:

H2. There is a positive relationship between interactive engagement and movie performance

4.3.3. The interaction of personal engagement and interactive engagement on movie performance

We focus on the complementary effects of personal engagement and interactive engagement because previous studies have examined their direct effects on movie performance (e.g., Oh et al., 2017) but they have not studied the interaction effect between them. Social media can be considered a WOM platform where information among users is exchanged, reducing information asymmetries in selling process. WOM is a manifestation of customer engagement (Van Doorn et al., 2010), which act as a dominant channel for raising customer awareness (Oh et al., 2017) and for gaining more profit. Previous literature has examined how customer engagement influence firm's profits, and it has identified personal engagement and interactive engagement as the two key customer engagement (Calder et al., 2009). Personal engagement and interactive engagement may involve higher intrinsic enjoyment to users from both the reinforcement of self-esteem and the utilitarian worth getting useful information and valuable input. This greater intrinsic enjoyment makes more likely that users choose the movie, increasing the movie performance of the firm.

When the users conduct a wider variety of actions such as read movie news, liking content, watching movie trailer (i.e., personal engagement), discuss and share content, or write comments about movies (i.e., interactive engagement) is engaged by both individual qualities and social relevance, thus the two customer engagements should operate as complement and generate synergies, increasing the level of engagement, and therefore the likelihood of users know well the movie and build an enduring relational exchange, increasing the loyalty and commitment and thus the probability of watching the movie. When users develop both personal and interactive engagements, they are more likely to watch the movie than when users develop one or the other alone. This leads us to hypothesize the following:

H3. Personal engagement and interactive engagement positively interact to impact movie performance.

4.4. Research context

Movies are generating interest among general public in Spain and UK. According to ComScore, Spanish cinema admissions in 2016 were more than 100 million, reaching a total box office of more than 600€ million (Belinchón, 2017). Meanwhile, according to BFI Research and Statistics Unit, UK cinema admissions in 2016 were more than 168 million, reaching a total box office of more than £1.329 million. Days before the release, users share their excitement, anticipation and opinion of upcoming movies by interacting with movie profiles and other users on social media channels such as Facebook, Twitter and YouTube (Oh et al., 2017).

We choose social media platforms because the effect of online WOM is more consistent with social media data than customer reviews. This may be due to the push-based nature of these communication platform, as opposed to traditional customer reviews which are pull-based communication platforms (Yoon et al., 2017). Push-based communication platform such as social media is related to the awareness effect, which refers to the WOM function to spread information among the users, influencing user's behavior just by informing them. Pull-based communication platforms such as traditional customer reviews are related to the persuasive effect, which refers to the WOM function to alter the preferences of the users toward the movie and affect their decision (i.e., users looking for movie reviews on specific movies tend to already know the existence of the movie) (Rui et al., 2013).

We chose Facebook, Twitter and YouTube because these social media platforms are the most used social media in Spain with a 27.07% for Facebook, 14.99% for Twitter, and 15.67% for YouTube in 2017 (Statista, 2018). Also, these social media platforms are the most used social media in UK with 32 million UK users for Facebook, 20 million UK users for Twitter, and 19.1 million UK users for YouTube (Social Media Marketing, 2017).

We decide do not to consider temporary social media, such as Slingshot, Cyberdust or the most well-known Snapchat, because even this type of social media is becoming increasingly important, their usage is not pervasive yet in the countries of our study (i.e., Spain and UK). For example, according to Statista, just 9% of the respondents have an active account on Snapchat, whereas 12% have an inactive or closed account, and 79% have no account at all in Spain in 2016. In UK, although the growth rate of Snapchat is high, it remains insignificant compare to other social media (Sweney, 2018). Then, we do not include temporary social media in our study.

4.4.1. Social media platforms: Facebook, Twitter and YouTube

Facebook is the biggest social network worldwide, which have more than 1.94 billion global monthly active users in the first quarter of 2017, and generated 27.64 billion U.S. dollars in revenues (Statista, 2018). Users in Facebook can create their own Facebook page, add other users, share updates and photos, send private messages, and participate in groups and events. They also can share, comment and like updates and photos from other Facebook pages. Firms can also create their own Facebook page, which may be used to address their customers directly. That is why marketers make effort to generate Facebook fans (Statista, 2018).

Twitter is one of the leading social networks worldwide, which have 328 million monthly active users in the first quarter of 2017, and generate 2.53 billion U.S. dollars in revenues (Statista, 2018).Users in Twitter can send short messages called tweets (historically the messages were limited to 140 characters, recently the limitation of characters has been restricted to 280), follow other Twitter profiles, send private messages, share an existing message called retweet, like an existing message and view other messages. Twitter usage is increasingly notable during events such as sporting events or television airings (Statista, 2018). Users can index keywords or topics in Twitter with hashtags, facilitating that users may easily follow the topic they are interested in. Firms make effort to recruit followers to be able to address them more directly. For example, the most popular fashion brand on Twitter in July 2017 was Chanel with more than 13 million of followers (Statista, 2018).

YouTube is a video-sharing platform which have a wide variety of user-generated and corporate media content. According to YouTube CEO Susan Wojcicki 1 billion hours of content are consumed on this platform every day. The most popular types of YouTube content include music videos, beauty and fashion tips, video blogs, and instructional videos. Firms, musicians, or movie's distributors might use YouTube in order to execute direct advertisement (Statista, 2018).

4.4.2. Prerelease customer engagement and movie performance

We consider the prerelease personal and interactive engagement. Liu (2006) suggests that WOM activities are the most active during a movie's prerealese and opening week, and WOM information offers explanatory power for movie performance.

Movie performance refers to the opening-weekend box office gross revenue (i.e., Friday, Saturday and Sunday of the release week). The highest earning time for most movies is at the time of release, specifically the opening weekend (Gopinath et al., 2013; Oh et al., 2017). So, it is meaningful to understand the predictive role of customer engagement via social media on movie performance.

4.5. Research methodology

4.5.1. Sample, data and measures

The proposed model was empirically tested with a sample of 966 movies released in the UK and Spanish market between December 2015 and November 2016. We removed those movies without movie performance data and those movies without social media data.

Movie industry is especially paramount in this context for several reasons. Understand how customer engagement may help firms to better forecast future sales and to develop effective targeting strategies is of vital importance since movie industry is highly risky and most of the movies produced are unprofitable (Luo, 2006; Vogel, 2001). Customer engagement is higher and more meaningful since movies are cultural goods with an experiential nature, which receive great public interest. Therefore, before watching a movie, it is difficult to evaluate the quality and drive customers to engage in WOM to gather information (Liu, 2006). A unique feature of the movie industry is that all weeks (while the movie is in theaters) are not considered equally important since many managerial decisions need to be made on a weekly basis (Liu, 2006). The highest earning time for most movies is at the time of release, specifically the opening weekend (Gopinath et al., 2013; Oh et al., 2017). It is meaningful to understand the predictive role of customer engagement via social media on movie performance.

To measure the different constructs included in our proposed model, we collected and used secondary data drawn from eleven databases (i.e., IMDb, Film Affinity, Sensacine, Estreno de Cine, Launching Films, Movie Insider, Facebook site, Twitter site, YouTube site, Tweetreach and Box Office Mojo) for one year between December 2015 and November 2016. We first collected the name of the movies which were going to be released from different databases. We used IMDb, Film Affinity, Sensacine and Estreno de Cine to collect the movies released in Spain, and we used IMDb, Launching Films and Movie Insider to collect the movies released in UK. Then, we used the name of each movie to gather information about these movies from the other databases.

4.5.1.1. Personal engagement

Personal engagement was measured as a composite first-order construct determined by Facebook likes, Twitter followers, YouTube views and YouTube likes. We collected the data the day before the release date. Facebook likes refer to the number of Facebook likes for the movie profile. Twitter followers was evaluated through the number of followers on Twitter for each movie profile. YouTube views was specified as the YouTube count of views for a particular video of each movie profile and YouTube likes as the YouTube count of likes for a particular video of each movie profile. These variables are metrics accumulated over time.

4.5.1.2. Interactive engagement

Interactive engagement was measured as a composite first-order construct determined by Facebook talks, Twitter tweets and YouTube comments. We also collect the data the day before the release date. Facebook talks refer to the number of unique users who have created what could be called a 'story' about the movie profile (i.e., users who have made at least one of the following actions: like a page, post on the page wall, like a post, comment on a post, share a post, write a recommendation…). Twitter tweets was specified as the count of public tweets sent by other Twitter profiles about the movie profile. It includes the number of mentions to the Twitter profile and the number of movie hashtags. YouTube comments was evaluated as the YouTube count of comments from YouTube viewers for a particular video of each movie profile.

4.5.1.3. The interaction term between personal engagement and interactive engagement

Orthogonal approach was used to measure the interaction term between personal engagement and interactive engagement by using the standardized residuals of independent variables as indicators of the interaction term.

4.5.1.4. Movie performance

Movie performance, the endogenous variable in this work, is a single indicator construct measured through the opening-weekend box-office gross revenue (i.e., the Friday, Saturday and Sunday of the first week). This construct was measured with information collected from boxOfficeMojo.com.

4.5.1.5. Control variables

We controlled for the effects of movie's distributor, month of release, country and theaters with information collected from boxOfficeMojo.com. Movie's distributor was measured as a composite construct shaped by 28 indicators created as follows (Benitez et al., 2017b). The movies were classified into 29 distributors determining Sony as the group reference. For each movie we created 28 dummy indicators (0: No, 1: Yes) referring to the 29 distributors with the exception of the reference distributor (i.e., Sony) in order to provide equidistant measures (Henseler et al., 2016; Benitez et al., 2017a). Then, movie's distributor was operationalized as a composite first-order construct shaped by 28 indicators. Month release as operationalized as a composite first-order construct shaped by 11 indicators and was measured by the same method we used to measure movie's distributor. The reference group of the month release was April. We specified country as a dummy variable (0: Spain, 1: UK). Theaters was measured as the natural logarithm of the number of theaters in which the movie was release.

4.6. Empirical analysis and results

The proposed research model was tested empirically by using PLS path modeling. This decision was statistically rational for the following reasons (Benitez et al., 2017). First, PLS path modeling is a full-fledged estimator to SEM and a well suited to effectively deal with composite model such as this proposed model. Second, PLS path modeling address multicollinearity among the variables in the proposed model (Jung & Park 2018), and potential sources of endogeneity (Hult et al., 2018). Third, since we performed a multi-group analysis to explore whether there are statistically significant differences between movies released in different countries (i.e., Spain and UK), PLS path modeling can be adequate for comparing different groups (Klesel et al., forthcoming; Sarstedt et al., 2011). We used the statistical software package Advanced Analysis for Composite (ADANCO) 2.0.1 Professional (https://www.composite-modeling.com/) (Henseler 2017a). ADANCO is a new software for variance-based SEM. This software implements the most updated developments in the PLS field (e.g., overall goodness-of-fit tests), and estimates composite models, common factors, and facilitates causal and predictive models (Rueda et al., 2017).

Prior to data collection, we performed a priori statistical power analysis to estimate the minimum sample size to have sufficient accuracy and statistical power to detect the effects of interest in the research model (Benitez et al., 2017). We assumed a medium effect size ($f^2 = 0.150$), a power level to achieve of 0.800 and an alpha level of 0.05. The highest number of predictors received by an endogenous variable in the research model was seven (the number of structural links received by movie performance in the research model). Based on the Cohen's power tables, the minimum required sample for the proposed model was 102. Our sample size was 966, much higher of the required sample size, suggesting that our sample size had sufficient statistical power.

4.6.1 Measurement model evaluation

There exist two types of theoretical concepts: behavioral concept from Behavioral Sciences and design concept from Design Science (Henseler 2017b). Behavioral constructs (i.e., latent variables), which may be operationalized as reflective (Bollen 1989) or causal-formative (Diamantopoulos 2011), assume causal relationships between the construct and their indicators. For reflective measurement, the construct causes its indicator, and for causal-formative, the indicators cause the construct. Theoretical constructs (i.e., artifacts), which are artificially created, are operationalized as composite (Henseler 2017b; Simon 1969). For composite measurement, the indicators are combined to make up the construct. Personal engagement, interactive engagement, and movie performance were conceptualized, operationalized, and measured as composite first-order constructs, thus the measurement and the structural models can be estimated and evaluated simultaneously (Henseler et al., 2016; Benitez et al., 2017). To evaluate the measurement model, we conducted a confirmatory composite analysis, and assessed multicollinearity, and weights and loadings and their level of significance of all constructs included in the research model.

First, we conducted a confirmatory composite analysis to test the goodness of overall fit of the saturated model (i.e., all constructs are freely correlated and the construct is specified by the analyst (Benitez et al., 2017). The confirmatory composite analysis checks the adequacy of the composite models by testing the discrepancies between the empirical correlation matrix and model-implied correlation matrix of the saturated model. This analysis is helpful because potential misfit in the model can be due to misspecifications in the composite models (Benitez et al., 2017). Various non-exclusive assessment procedures of model fit can be considered, i.e., approximate fit measures such as the SRMR, and bootstrap-based exact fit measures such as the 95% quantile of the unweighted least squares (d_{ULS}) and geodesic discrepancy (d_G) between the empirical and the model-implied correlation matrix (Henseler et al., 2014, Benitez et al., 2017). Confirmatory composite analysis also enables to detect potential misspecification (Henseler et al., 2016). Table 4.2 shows the results of this analysis. All discrepancies are below the 95%-quantile of the bootstrap discrepancies, thus the saturated model should be not rejected based on an alpha level of 0.05, which suggests a very good measurement model fit. These results suggested empirical support for the structure of composites of the measurement model.

Table 4.2: Results of the confirmatory composite analysis

Discrepancy	First-order constructs			Control variables		
	Value	HI95	Conclusion	Value	HI95	Conclusion
SRMR	0.076	0.094	Supported	0.020	0.022	Supported
d_{ULS}	0.208	0.318	Supported	0.345	0.407	Supported
d_G	0.081	0.159	Supported	0.072	0.082	Supported

Then, we estimated the variance inflation factors (VIFs) values to evaluate the multicollinearity of the composite indicators. VIF values ranged from 1.046 to 4.359, which are below 10 (Benitez et al., 2017), suggesting that multicollinearity is not a problem in our data.

To check the indicator weights and loadings and their level of significance we conducted a bootstrap analysis with 4999 subsamples. Weights refer to the relative importance of an indicator to its construct, while loadings refer to the absolute importance of an indicator to its construct (Benitez et al., 2018; Cenfetelli & Bassellier, 2009). Indicators weights are expected to be significant. However, non-significant indicators weights are not a problem when their loadings are significant. Moreover, indicators with non-significant weights or loadings may be kept to preserve content validity (Hair et al., 2017; Benitez et al., 2017).

All indicator loadings were significant at 0.01 level. All indicator weights were significant except one indicator for interactive engagement. As the loading of this indicator was significant, this indicator was retained in the empirical analysis (Cenfetelli & Basellier, 2009). Overall, all constructs included in this study exhibited good measurement properties. Table 4.3 shows the result of the measurement model evaluation. After that, we proceeded with the test of hypotheses and the evaluation of the structural model.

Table 4.3: Measurement model evaluation

Construct/indicator	Mean	S.D.	VIF	Weight	Loading
Personal engagement					
Facebook likes	371,670	1,607,155	1.433	0.240***	0.407***
Twitter followers	38,132.93	352,489.8	1.427	0.116†	0.338***
YouTube views	1,466,986	4,410,196	4.359	0.494***	0.930***
YouTube likes	8,384.59	36,351.44	4.299	0.446***	0.906***
Interactive engagement					
Facebook talks	25,184	79,890.29	1.046	0.341**	0.525***
Twitter tweets	959.43	1,401.35	1.289	0.832***	0.939***
YouTube comments	1,078.41	8,773.40	1.248	0.081	0.489**
Movie performance	736,087.4	2,787,723			
Movie's distributor: The distributor of the movie	0.032	0.177			
Month release: The month in which the movie has been released	0.081	0.273			
Country: Spain vs. UK	0.569	0.495			
Theaters: Natural logarithm of the number of theaters in which the movie was release	3.688	1.824			

Note: †$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ [based on t(4998), one-tailed test].

4.6.2. Structural model evaluation

To test the hypotheses and evaluate the structural model we examined the beta coefficients, the significance of the proposed relationships the R^2 and adjusted R^2 values, the overall fit of the estimated model, and the effect size (f^2) for each relationship (Henseler et al., 2016; Benitez et al., 2017). To do that, we run a bootstrap analysis with 4,999 subsamples. We study two models to test the hypothesized relationships. First, to analyze the relationships between personal engagement and movie performance (H1), and interactive engagement and movie performance (H2), we assessed a baseline model, which include these direct relationships, and the relationships between the control variables and movie performance. Second, we consider Model 1 to analyze the relationship between the interaction effect between personal engagement and interactive engagement, and movie performance (H3). Model 1 adds the interaction effect between personal engagement and interactive engagement to the baseline model. We found support for all proposed hypotheses. The empirical analysis suggests that both personal engagement (H1) (β = 0.288, $p_{one\text{-}tailed} < 0.050$) and interactive engagement (H2) (β = 0.303, $p_{one\text{-}tailed} < 0.001$) improve movie performance. Similarly, the interaction between personal engagement and interactive engagement also improves movie performance (H3) (β = 0.267, $p_{one\text{-}tailed} < 0.050$). Table 4.4 and Figure 4.1 present the results of the test of hypotheses.

Regarding to control variable, we found the following results. Movie performance was influenced by movie's distributor (β = 0.247, $p_{one\text{-}tailed} < 0.001$) what it means that the movie performance depends on the distributor who has made the movie. Also, it depends on the country (β = 0.102, $p_{one\text{-}tailed} < 0.001$) being higher in UK than in Spain. Moreover, movie performance depends on the number of theaters in which movie is released in its opening. However, we did not find any relationship between the month release and movie performance, showing that Spanish and British viewers were not sensitive to the month of release. This may be due to the availability of the movies throughout the year, independently of the month.

The R^2 value and the adjusted R^2 for movie performance were evaluated. The R^2 values was 0.507 and the adjusted R^2 was 0.504 for baseline model, and the R^2 values was 0.574 and the adjusted R^2 was 0.577 for Model 1. Also, we evaluated the goodness of model fit for the structural model by evaluating the discrepancy between the empirical correlation matrix and the model-implied correlation matrix of the estimated model (Benitez et al., 2017b; Henseler, 2015). The SRMR value of the proposed model was 0.035 for the baseline model, and 0.036 for Model 1 (lower than 0.080), and all discrepancies were below the 95%-quantile of the bootstrap discrepancies, thus the proposed model present very good model fit since it should not be rejected based on the alpha level of 0.05 (Henseler, 2017a). The f^2 values of the hypothesized relationships ranged from 0.103 to 0.114 for baseline model, and 0.095 to 0.157 for Model 1, indicating weak-medium effect sizes between the exogenous and endogenous variables in the proposed model (Henseler & Fassott, 2010). Correlation matrix is given in Table 4.5.

Table 4.4: Structural model assessment

Beta coefficient	Baseline model		Model 1	
Personal engagement → Movie performance (H1)	0.288* (1.969) [-0.059, 0.507]		0.258** (2.431) [-0.022, 0.386]	
Interactive engagement → Movie performance (H2)	0.303*** (2.934) [0.094, 0.506]		0.309*** (3.021) [0.097, 0.523]	
Personal engagement * Interactive engagement → Movie performance (H3)			0.267* (1.676) [-0.104, 0.411]	
Movie's distributor → Movie performance (CV)	0.242*** (4.536) [0.166, 0.377]		0.247*** (4.475) [0.154, 0.371]	
Month release → Movie performance (CV)	0.027 (0.582) [-0.075, 0.098]		0.002 (0.047) [-0.074, 0.095]	
Country → Movie performance (CV)	0.066* (1.786) [0.007, 0.138]		0.102*** (4.995) [0.059, 0.139]	
Theaters → Movie performance (CV)	0.119** (2.428) [0.045, 0.219]		0.176*** (6.465) [0.117, 0.222]	
Endogenous variable	**R^2**	**Adjusted R^2**	**R^2**	**Adjusted R^2**
Movie performance	0.507	0.504	0.574	0.577
Discrepancy				
SRMR value	0.035		0.036	
SRMR HI_{99}	0.037		0.040	
d_{ULS} value	1.477		1.688	
d_{ULS} HI_{99}	1.642		2.059	
d_G value	0.361		0.397	
d_G HI_{99}	0.770		1.235	
f^2				
Personal engagement → Movie performance (H1)	0.103		0.095	
Interactive engagement → Movie performance (H2)	0.114		0.137	
Personal engagement * Interactive engagement (H3)			0.157	
Movie's distributor → Movie performance (CV)	0.082		0.099	

Beta coefficient	Baseline model	Model 1
Month release → Movie performance (CV)	0.001	0.000
Country → Movie performance (CV)	0.008	0.022
Theaters → Movie performance (CV)	0.020	0.049

Note: t-values in parentheses. Bootstrapping 95% confidence interval bias corrected in square bracket (based on n = 5000 subsamples). $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ [based on t(4999), one-tailed test]. T(0.05, 4999) = 1.645; t(0.01, 4999) = 2.327; t(0.001, 4999) = 3.092.

Figure 4.1: Conceptual model

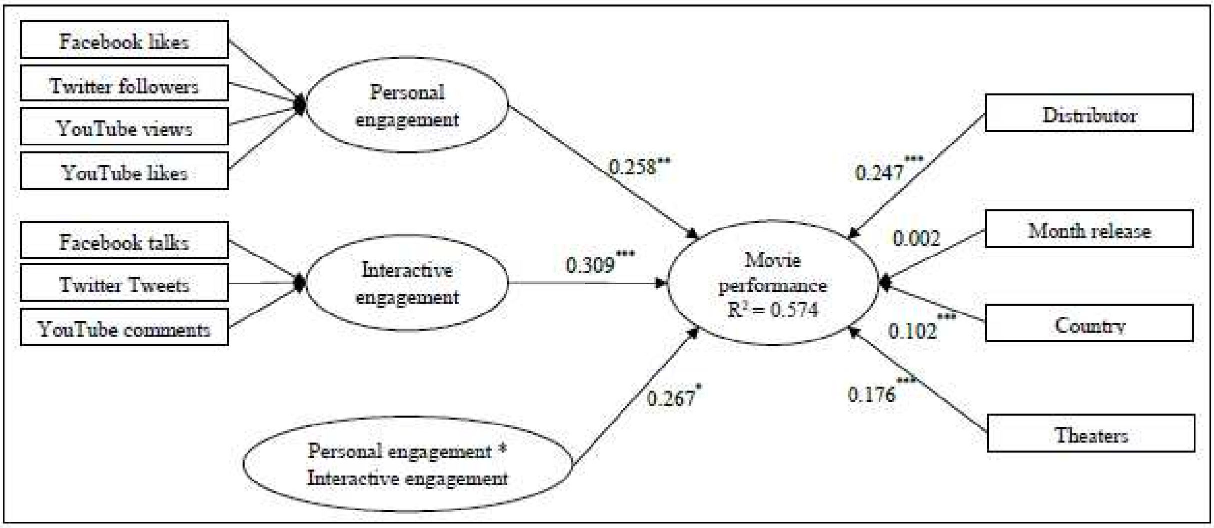

Table 4.5: Correlation matrix

	1	2	3	4	5	6	7
1. Personal engagement	1.000						
2. Interactive engagement	0.663	1.000					
3. Movie performance	0.551	0.561	1.000				
4. Movie's distributor	0.197	0.240	0.371	1.000			
5. Month release	0.023	0.036	0.047	0.103	1.000		
6. Country	0.186	0.066	0.106	-0.059	-0.099	1.000	
7. Theaters	0.252	0.262	0.368	0.624	0.027	-0.172	1.000

4.6.3. Test of robustness

The robustness of the proposed model was tested by estimating an alternative model with its corresponding mediation analysis. In this alternative model, we assumed that personal engagement enables the interactive engagement, which in turn affects the movie performance. The overall fit of this alternative model is worse than the overall fit of the proposed model since the alternative model fitted only with a probability of 1% while the proposed model (Model 1) fitted with a probability of 5%.

4.6.4. Post-hoc multi-group analysis

We explored whether there were statistically significant differences between movies released in Spain and UK. To check these potential differences, we performed a post hoc multi-group analysis. Values, which may be shared by people within a culture, shape individuals' interpretations of stimuli and thus their behavior. These differences among cultures may explain systematic differences in customer engagement (Brumbaugh, 2002). Customer engagement via social media is mainly related to two dimensions of Hofstede (1980)'s framework: uncertainty avoidance and individualism. Uncertainty avoidance refers to the extent to which members of a national culture feel uncomfortable by ambiguous or unknown situations. In low uncertainty avoidance cultures such as UK, users are more likely to be active information seekers as opposed to high uncertainty avoidance cultures such as Spain (Mooij & Hofstede, 2002). Individualism refers to the extent to which a society maintains interdependence among its members. Thus, in low individualist (i.e., collectivist) cultures such as Spain, members are more likely to look after the interest of his or her ingroup, and have opinions and beliefs of them as opposed to high individualist cultures such as UK. Therefore, customer engagement via social media for UK and Spain may be quite similar since the two main dimensions affecting it are opposed. We did not find differences between these countries in any relationships. This lack of differences may be due to the opposed effects of uncertainty avoidance and individualism on customer engagement via social media. Spain is a collectivist culture which makes users to be more "engaged", in the same way that UK is a low uncertainty avoidance culture which also makes users to be more "engaged".

4.7. Discussion and conclusions

4.7.1. Key contributions to IS Research

This investigation examines the predictive roles of personal engagement and interactive engagement on movie's opening box office revenue, and the complementary role of both engagements in this equation. The proposed theory was tested on a sample composed of 966 movies released in the UK and Spanish market between December 2015 and November 2016, and the empirical analysis suggests that personal engagement and interactive engagement can impact on movie performance. We also find that personal engagement and interactive engagement interact to enable movie performance. The empirical analysis thus supports our proposed theory (i.e., personal engagement and interactive engagement influence movie performance, and both engagement are mutually reinforcing on their influence on performance).

This research makes three major contributions. First, most of the previous studies analyze the effect of WOM generated via social media on movies already released. Instead, we focus on the effect of WOM generated via social media before movies are released. A unique feature of the movie industry is that all weeks are not considered equally important since many managerial decisions need to be made on a weekly basis (Liu 2006). The highest earning time for most movies is at the time of release, specifically the opening weekend (Gopinath et al., 2013; Oh et al., 2017), that is why it is important to know the role of customer engagement on social media in predicting movie performance.

Second, with a few exceptions (e.g., Oh et al., 2017), research on the impact of customer engagement via social media on movie performance considering multiple channels is very limited. Our paper provides new evidence on how personal and interactive engagement influences movie performance. Unlike prior research, we focus on multiple social media channels (i.e., Facebook, Twitter and YouTube). Moreover, previous studies focus exclusively on U.S. movie industry (e.g., Duan et al., 2013; Gopinath et al., 2013; Yoon et al., 2017), leaving other impactful markets such as UK and Spain relatively unexplored. As such, this study examines the effectiveness of personal engagement and interactive engagement on economic performance on UK and Spanish markets.

Third, there is no study investigating the interaction role of personal engagement and interactive engagement on movie's future box-office economic performance. This work furthers our understanding in how personal and interactive engagement interact to impact on movie performance.

4.7.2. Limitations and future research directions

Despite the significant contributions of this study, our findings must be considered in the light of several limitations. First, our findings can be only generalized to movies released in the UK and Spanish market. We have not explored whether the proposed theoretical model is supported in samples of movie of other markets. Second, we analyzed three of the most popular external social media sites but did not examine the role of other social media sites such as temporary social media sites (e.g., Snapchat). Future research should extend our theory by using different context.

4.7.3. Managerial implications

The findings of this research provide two critical lessons for managers. Managers should consider social media as an effective tool to drive customer engagement and improve economic performance. Pre-consumption customer engagement has a lot to say about future movie sales. First, it suggests thus that firms must invest and develop strategies on social media to generate both personal and interactive engagement, and must consider this customer engagement behavior on social media sites such as Facebook, Twitter and YouTube, and incorporate that information to better forecast future sales (Rui et al., 2013). Second, as our results suggest, customer engagement impact on future sales, thus managers may encourage personal and interactive engagement in which people express their purchase intentions, opinions, and believes on social media sites such as Facebook, Twitter and YouTube. Managers must have the ability to use cohesive social media strategies across different channels (Oh et al., 2017). This is especially important before the movie release time since this is the moment when the highest earnings are arisen (Gopinath et al., 2013; Oh et al., 2017).

4.8. References

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5 CONCLUSIONES E IMPLICACIONES

5. CONCLUSIONES E IMPLICACIONES

Introducción

En un artículo directivo publicado en la revista directiva *MIT Sloan Management Review*, Kane y otros autores (2014) exploran la importancia que tienen las iniciativas de negocio en medios sociales para la obtención de valor. Dicho estudio se basa en encuestas anuales, análisis de datos y entrevistas con ejecutivos y académicos realizadas conjuntamente por *MIT Sloan Management Review* y Deloitte. Los resultados muestran que más del 60% de los directivos encuestados reportan que sus iniciativas de negocio en medios sociales ayudan al éxito en el cumplimiento de los objetivos establecidos así como afectan de forma positiva al desempeño empresarial. Estos resultados sugieren que muchas empresas están generando valor debido a sus iniciativas de negocio a través de los medios sociales (Kane et al., 2014). Por tanto, se pone de manifiesto el papel de los medios sociales como generadores de valor de negocio en las empresas.

Por ello, las preguntas de investigación planteadas a las que se pretende dar respuesta son: ¿la capacidad de medios sociales ayuda a las empresas a generar valor y mejorar los resultados organizativos? ¿qué mecanismos y capacidades intermedias y complementarias son necesarios para que la capacidad de medios sociales repercuta de forma positiva en la generación de valor y mejora de los resultados corporativos? Al dar respuesta a estas preguntas se aborda la discusión de los resultados de la tesis doctoral de forma global, y la discusión de los resultados propios de cada trabajo de investigación específico que forma dicha tesis. Además, se plantean las contribuciones académicas y las implicaciones directivas de dicho trabajo de investigación, junto con las limitaciones del mismo y las futuras líneas de investigación que se pueden desarrollar. Por último, dicho trabajo de tesis expone una síntesis de las consideraciones finales del mismo.

5.1. Conclusiones

Este trabajo de investigación muestra cómo la capacidad de medios sociales puede jugar un papel clave en la generación de valor de negocio en las empresas. El análisis del uso de los medios sociales (más allá del marketing) como generador de valor de negocio responde a la necesidad de profundizar en el mismo en detalle, tal y como ha sido reclamado en la literatura (Aral et al., 2013; Braojos et al., 2015; Leidner et al., 2010).

La capacidad de medios sociales hace referencia a la capacidad de la empresa en usar los medios sociales para actividades corporativas con fines de negocio. Estudios previos, tomando en consideración la perspectiva de las capacidades organizativas facilitadas por la TI, sugieren que la TI es una herramienta fundamental en la generación de valor de negocio. Esta creación de valor por parte de la TI es debida a mecanismos intermedios que intervienen en dicho proceso, tales como flexibilidad, integración de la cadena de suministro, gestión del talento, aprendizaje organizativo y gestión del conocimiento (ej., Ajamieh et al., 2016; Benitez et al., 2015; Benitez et al., 2018). Los resultados de este trabajo de investigación contribuyen a confirmar dicha perspectiva, además de profundizar en el conocimiento del tema objeto de estudio. Este trabajo arroja luz en el papel que tienen los medios sociales para crear valor tomando en consideración una serie de mecanismos y recursos y capacidades intermedias y complementarias que se relacionan con dicha capacidad.

En general, cabe concluir que la relación existente entre la capacidad de medios sociales y la creación de valor en las empresas es compleja y requiere considerar una serie de mecanismos y de recursos y capacidades intermedias y complementarias como la ambidestreza de conocimiento o el talento analítico de negocio, o cómo ésta sirve de herramienta para el *engagement* del consumidor.

A continuación, se recogen las conclusiones específicas que se derivan de cada uno de los trabajos de investigación que forman esta tesis doctoral.

En el Capítulo 2, los resultados obtenidos sugieren que la infraestructura de TI impacta en el desempeño innovador de la empresa a través de la ambidestreza de conocimiento. La infraestructura de TI sirve de apoyo a la empresa para la gestión de la información, ayudando a la conversión de dicha información en nuevo conocimiento (Mithas et al., 2011), y además ayuda a la empresa a compartir conocimiento dentro de la empresa (Pavlou & El Sawy, 2006). Todo esto hace que la empresa sea capaz de entender mejor el conocimiento complejo (Joshi et al., 2010), y de que exista una mayor cantidad de conocimiento nuevo en la empresa (Henderson & Clark, 1990), provocando un efecto positivo en el desempeño innovador de la misma. Esta es la primera vez que se aúna en un mismo trabajo la relación existente entre la infraestructura de TI, la ambidestreza de conocimiento y el desempeño innovador

En este capítulo, se evidencia también el papel que juega la capacidad de medios sociales en estas relaciones, mostrando el rol amplificador que juega en la relación existente entre la infraestructura de TI y la ambidestreza del conocimiento. La infraestructura de TI y la capacidad de medios sociales se autorrefuerzan para permitir en mayor medida la ambidestreza de conocimiento en la empresa.

En el Capítulo 3, los resultados muestran que la aplicación efectiva de los medios sociales afectará al desempeño innovador de la empresa si las empresas son ambidiestras en su gestión del conocimiento. Este resultado puede deberse a que la capacidad de medios sociales facilita a las empresas el adquirir conocimiento de los consumidores, competidores, empleados y proveedores, y provee con mayor flexibilidad a la empresa; además mejora el repositorio de conocimiento de la empresa para explotar dicho conocimiento de forma más fácil. Esta ambidestreza permite a la empresa logar un mayor desempeño innovador porque la explotación de nuevo conocimiento incrementa la diversidad y la heterogeneidad del conocimiento de la empresa; y usar y refinar dicho conocimiento ayuda a la empresa a entender y facilitar la identificación del conocimiento clave y valioso. Por tanto, las empresas pueden identificar conocimiento clave y valioso de sus grupos de interés, y aplicar y usar este conocimiento útil para innovar más y mejor.

Además, en este capítulo, también se muestra el papel que juega el talento analítico de negocio en estas relaciones, mostrando el efecto moderador que provoca en las relaciones entre la capacidad de medios sociales y la ambidestreza de conocimiento, y entre dicha ambidestreza de conocimiento y el desempeño innovador de la empresa. Por tanto, el talento analítico de negocio se complementa con la capacidad de medios sociales, y con la ambidestreza de conocimiento para provocar un efecto superior en el desempeño innovador de la empresa.

En el Capítulo 4, los resultados obtenidos sugieren que el *engagement* del consumidor, tanto el personal como el interactivo, impactan en el desempeño de las películas, haciendo que el desempeño empresarial de las mismas sea superior. Estas relaciones se pueden argumentar debido a que el *engagement* del consumidor provoca un sentimiento de pertenencia con dicha comunidad (i.e., *engagement* personal), y crea mejores experiencias para el usuario incrementando el conocimiento y la familiaridad sobre la película (i.e., *engagement* interactivo) (Oh et al., 2017) y, por tanto, incrementando la probabilidad de que la vean.

Además, este capítulo evidencia el efecto de interacción existente entre ambos *engagement* del consumidor. Esto quiere decir que el *engagement* personal y el *engagement* interactivo del consumidor interaccionan y se complementan de tal forma que dicha interacción provoca un nivel de *engagement* del consumidor superior, y por tanto mayor probabilidad de que los usuarios conozcan bien la película y construyan una relación de intercambio duradera, incrementando la lealtad y el compromiso y en última instancia las posibilidades de ver la película.

5.2. Implicaciones del trabajo de investigación para el ámbito académico

Esta tesis doctoral supone una novedosa aportación a la literatura de Sistemas de Información. De forma más específica, supone una contribución a la literatura de valor de negocio de la TI, profundizando en el conocimiento de un recurso específico de TI, la capacidad de medios sociales, y su papel en la creación de valor de negocio. Además, dicha tesis doctoral contribuye con la literatura de la ambidestreza de conocimiento en la empresa, a la literatura del talento analítico de negocio, y a la del *engagement* del consumidor. Estas contribuciones son fruto de dar respuesta a una serie de interrogantes: *si ayuda o no la capacidad de medios sociales a las empresas a generar valor y mejorar sus resultados organizativos, y qué mecanismos y capacidades intermedias y complementarias son necesarias para que la capacidad de medios sociales repercuta de forma positiva en la generación de valor y mejora de dichos resultados empresariales.* Por tanto, esta investigación, partiendo de la perspectiva de las capacidades organizativas facilitadas por la TI (Benitez & Walczuch, 2012), y la perspectiva de la complementariedad entre recursos (Ennen & Richter, 2010), contribuye a dilucidar mecanismos y capacidades claves importantes en el papel de la capacidad de medios sociales como creadora de valor de negocio en las empresas, y arroja luz al fenómeno de gran interés social en la actualidad como es el efecto de la capacidad de medios sociales en el desempeño organizativo.

A continuación, se detallan las implicaciones de naturaleza teórica y empírica de este trabajo de investigación.

5.2.1. Contribuciones teóricas y empíricas

Este trabajo aporta una serie de contribuciones a la literatura de Sistemas de Información. Primero, provee nuevas evidencias teóricas para desarrollar una explicación de cómo la infraestructura de TI afecta al desempeño innovador de la empresa. Para ello, se centra en la ambidestreza de conocimiento de la empresa como variable mediadora. Esto significa que el efecto que tiene la infraestructura de TI en el desempeño innovador es a través de la ambidestreza de conocimiento, por lo que la infraestructura de TI permite la gestión del conocimiento organizativo para incrementar el desempeño innovador. Este estudio aúna por primera vez, en un mismo estudio, el análisis del impacto de la infraestructura de TI en la ambidestreza de conocimiento y en las actividades de innovación.

Segundo, este estudio teoriza cómo la capacidad de medios sociales modera la relación existente entre la infraestructura de TI y la ambidestreza de conocimiento. El campo de investigación de los Sistemas de Información necesita teorías y estudios empíricos que expliquen cómo la capacidad de medios sociales crea valor de negocio a través de la amplificación en el impacto de usar la infraestructura técnica y humana de TI para explorar y explotar conocimiento con propósitos organizativos. Además, el conocimiento sobre el papel de los medios sociales en la creación de valor de negocio en las empresas a través del impulso de las actividades de innovación es limitado en estudios previos. Por ello, este estudio contribuye con la necesidad de estudiar el uso de los medios sociales en apoyo a las actividades de innovación de las empresas. Por un lado, esta tesis doctoral argumenta de forma teórica y demuestra de forma empírica que la creación de valor de negocio por parte de la capacidad de medios sociales es un efecto indirecto en el desempeño organizativo a través del refuerzo del efecto de la infraestructura de TI en la ambidestreza de conocimiento, el cual a su vez mejora el desempeño innovador. Por otro lado, este estudio también explica de forma teórica y muestra empíricamente el papel facilitador de la capacidad de medios sociales en el desempeño innovador a través de la ambidestreza de conocimiento. Por tanto, esta tesis doctoral analiza tanto el papel complementario de la capacidad de medios sociales sobre el impacto de la infraestructura de TI en el desempeño innovador, como el papel facilitador de la capacidad de medios sociales sobre el desempeño innovador, centrándonos en la ambidestreza de conocimiento.

Tercero, partiendo del artículo directivo de Ransbotham y otros (2015), este estudio desarrolla de forma teórica el concepto y las medidas de talento analítico de negocio. Se conceptualiza el término de talento analítico de negocio como el talento de la empresa en aplicar analítica de negocio de forma efectiva mediante la transformación de datos en conocimiento valioso para apoyar las actividades de negocio (Ransbotham et al., 2015). La medida se ha construido con datos secundarios recogidos de la base de datos LexisNexis, usando las noticias publicadas sobre la empresa. Por tanto, este estudio delimita el concepto y sus indicadores, y confirma la validez para dicho constructo. Además, muestra cómo este talento analítico de negocio amplifica la relación existente entre la capacidad de medios sociales y la ambidestreza de conocimiento, y la relación establecida entre la ambidestreza de conocimiento y el desempeño innovador.

Cuarto, la mayoría de estudios previos en el contexto cinematográfico analizan el efecto del boca a boca a través de las redes sociales en películas ya estrenadas y considerando un único canal. Sin embargo, junto con contadas excepciones (ej., Oh et al., 2017), este estudio se centra en analizar el efecto del boca a boca a través de los medios sociales con anterioridad a que la película se haya estrenado para conocer el papel que tiene el *engagement* del consumidor a través de los medios sociales en la predicción del desempeño organizativo en la industria del cine. En la misma línea, analizamos el impacto de este *engagement* del consumidor a través de las redes sociales en el desempeño organizativo considerando múltiples canales como Facebook, Twitter y YouTube. Además, estudios previos se han centrado en la industria del cine en Estados Unidos dejando otros mercados cinematográficos importantes sin explorar. Por ello, este estudio examina la efectividad que tiene el *engagement* del consumidor, tanto el *engagement* personal como el interactivo, en el desempeño considerando los mercados de España y Reino Unido.

Quinto, este trabajo contribuye con la literatura de la complementariedad de recursos en el campo de Sistemas de Información argumentando el rol complementario que existe entre la capacidad de medios sociales y otros recursos/capacidades. Concretamente, este trabajo apunta al rol complementario que existe entre la capacidad de medios sociales y la infraestructura de TI, donde ambas se complementan para amplificar el impacto sobre la ambidestreza de conocimiento y, además, el rol complementario que existe entre la capacidad de medios sociales y el talento analítico de negocio de las empresas en su impacto en la ambidestreza de conocimiento. Esta tesis doctoral también aporta a la literatura de la complementariedad de recursos considerando la complementariedad existente entre la ambidestreza de conocimiento y el talento analítico de negocio mejorando el desempeño innovador de la empresa. Otra de las contribuciones de esta tesis doctoral a la literatura de la complementariedad de recursos es el papel complementario que juegan el *engagement* personal y el *engagement* interactivo en su impacto en el desempeño de las películas en la industria cinematográfica.

5.3. Implicaciones para la práctica empresarial

De este trabajo de investigación se derivan una serie de aportaciones de interés para el ámbito empresarial, ya que aporta conocimiento de cómo los medios sociales pueden ayudar a las empresas a crear valor de negocio. Las implicaciones que se extraen de los resultados obtenidos de esta investigación son de especial importancia para los directivos de Sistemas de Información. Podemos destacar tres grandes implicaciones directivas. En primer lugar, la infraestructura técnica y humana de TI provee la base para explorar y explotar el conocimiento, así como cambiar y desarrollar productos y procesos más eficientes. En este sentido, es aconsejable que las empresas desarrollen una infraestructura técnica y humana de TI que les permita explorar y explotar el conocimiento de forma simultánea y, por tanto, desarrollar ambidestreza de conocimiento que les ayude a innovar más y mejor. Asimismo, es fundamental desarrollar la capacidad de medios sociales en conjunto con la infraestructura técnica y humana de TI para poder conseguir un mayor efecto en la ambidestreza de conocimiento de la empresa. Por tanto, este estudio muestra la importancia del desarrollo conjunto de la infraestructura de TI y la capacidad de medios sociales para conseguir una mayor exploración y explotación del conocimiento, fundamental para la mejora del desempeño innovador de la empresa.

En segundo lugar, el desarrollo de la capacidad de medios sociales ayuda a las empresas a ser ambidiestras en su gestión del conocimiento, lo que a su vez mejorará el desempeño innovador de las mismas. Por tanto, los directivos deben ser conscientes de los beneficios asociados al desarrollo de la capacidad de medios sociales en la adquisición de datos y comunicar sus iniciativas para poder explorar y explotar el conocimiento con el fin de innovar más y mejor. En este sentido, los directivos deberían invertir, desarrollar y hacer uso de los medios sociales para adquirir y compartir conocimiento para innovar. Además, las empresas pueden amplificar el impacto de la capacidad de medios sociales en la ambidestreza de conocimiento y el impacto de esta ambidestreza de conocimiento en el desempeño innovador si la empresa tiene talento analítico de negocio. En este sentido, los directivos deberían tener en consideración la importancia de desarrollar talento analítico de negocio, siendo conscientes de la escasez de este talento en el mercado. Por ello, los directivos deberían hacer un esfuerzo extra en atraer y retener personal especializado en analítica de negocio y formar a aquellos que muestren alto potencial. Aquellas empresas que tengan talento analítico de negocio pueden beneficiarse en mayor medida de los medios sociales y de la ambidestreza de conocimiento. Esto es debido a que el talento analítico de negocio se complementa, por un lado, con la capacidad de medios sociales amplificando su impacto en la ambidestreza de conocimiento y, por otro, con la ambidestreza de conocimiento provocando una mejora en el desempeño innovador de la empresa.

En tercer lugar, directivos deberían considerar los medios sociales como una herramienta efectiva para impulsar el *engagement* del consumidor y mejorar los resultados económicos. El *engagement* del consumidor antes de consumir una película tiene mucho que decir sobre las futuras ventas de la misma; por tanto, los directivos deben invertir y desarrollar estrategias en los medios sociales para generar *engagement* personal e interactivo y deben considerar tal *engagement* en plataformas como Facebook, Twitter y YouTube e incorporar esa información para ser capaz de predecir las ventas futuras (Rui et al., 2013). Siguiendo la misma argumentación y, tal y como nuestros resultados sugieren, los directivos deben motivar e incentivar el *engagement* personal e interactivo del consumidor en el que los consumidores expresen sus intenciones de compra, sus opiniones y creencias en medios sociales. Los directivos de TI deben tener la habilidad de usar de forma cohesionada estrategias de medios sociales en los diferentes canales (Oh et al., 2017). Esto es especialmente con anterioridad a que la película se estrene ya que en este momento es cuando se dan las mayores ganancias (Gopinath et al., 2013; Oh et al., 2017).

5.4. Limitaciones y futuras líneas de investigación

Los resultados de esta investigación, a pesar de aportar importantes contribuciones teóricas y prácticas, deben ser interpretados con cautela ya que no están exentos de limitaciones. Dichas limitaciones deben ser consideradas como áreas a tener en cuenta en futuras líneas de investigación. Las principales limitaciones de este estudio son las siguientes:

Primero, debido a la complejidad que caracteriza al "mundo real", es imposible contemplar todos los posibles factores que condicionan o influencian las variables endógenas (Huertas, 2017). Distintos son los factores que pueden intervenir en el contexto de la creación de valor de negocio a través de los medios sociales. Por ello, la consideración de otras variables puede ayudar a comprender mejor los mecanismos por los cuales la capacidad de medios sociales afecta de forma directa o indirecta a la creación de valor de negocio en las empresas. Por lo tanto, futuras líneas de investigación pueden incluir nuevas variables que puedan influir en el contexto de los medios sociales como generador de valor de negocio.

Segundo, para este estudio se han empleado dos muestras. Por un lado, la correspondiente al Capítulo 2 y al Capítulo 3, para la cual se han usado datos secundarios de 100 empresas pequeñas estadounidenses para explorar el papel facilitador y moderador de la capacidad de medios sociales en el contexto de la ambidestreza de conocimiento y del desempeño innovador. Por otro lado, la muestra empleada para el Capítulo 4, en la que se han usado datos secundarios de 966 películas estrenadas en España y en Reino Unido para analizar el impacto que tiene el *engagement* del consumidor a través de los medios sociales en el desempeño de las películas. Por tanto, la interpretación de los resultados puede ser generalizada, por un lado, a pequeñas empresas estadounidenses y, por otro, al contexto de la industria del cine en los mercados de España y Reino Unido. Por este motivo, futuras líneas de investigación deberían analizar si los resultados e implicaciones de este estudio son estables en otros contextos geográficos y en otra tipología de empresa para recoger las posibles diferencias fruto del contexto geográfico en el que se enmarca el estudio y del tipo de empresa que se considera.

Tercero, a pesar de que tenemos en consideración algunos de los medios sociales externos más populares (i.e., Facebook, Twitter, blogs, YouTube), nuestro estudio no examina el papel que juega los medios sociales internos en la creación de valor de negocio. Por ello, sería interesante para futuras líneas de investigación que analizaran si las plataformas sociales internas afectan a la creación de valor y en caso afirmativo, cómo se lleva a cabo esta influencia en el desempeño organizativo. Además, estudios futuros podrían considerar otros medios sociales externos como por ejemplo las plataformas sociales estrictamente profesionales como LinkedIn, las plataformas sociales empresariales como Microsoft Yammer o las plataformas sociales temporales como Instagram o Snapchat.

Por último, los análisis empíricos realizados son de naturaleza transversal, es decir, plasma las relaciones existentes en un momento determinado, por lo que no podemos hacer interpretaciones derivadas de la evolución de dichos factores a lo largo del tiempo, ni establecer tendencias. Por este motivo, estudios futuros podrían replicar dicho estudio usando datos de corte longitudinal para proporcionar un mayor entendimiento del papel de los medios sociales en la creación de valor de negocio de las empresas a largo plazo.

5.5. Consideraciones finales

La presente tesis doctoral supone un novedoso trabajo en el ámbito académico y en la práctica empresarial debido a la gran importancia de los medios sociales hoy en día. La rápida proliferación y la importante magnitud del uso de los medios sociales, alcanzando alrededor de un 37% de la población de la Tierra como usuarios, sugiere el potencial de dicha herramienta para la creación de valor de negocio en las empresas. Esta investigación doctoral pone de manifiesto el papel clave que juegan los medios sociales en la creación de valor de negocio en las empresas y en la mejora de sus resultados organizativos, y explica los mecanismos y capacidades intermedias y complementarias que son necesarias para que dichos medios sociales repercutan de forma positiva en esta generación de valor de negocio.

En una era caracterizada por la turbulencia, en la que el 90% de los datos existentes en el mundo fueron generados en los últimos dos años, es importante tener herramientas como los medios sociales que nos permitan hacer un uso efectivo de esta masa de información para mejorar el desempeño organizativo. Como reconocía el presidente ejecutivo de la empresa Cisco System, John Chambers, *"Al menos el 40% de todos los negocios morirán en los siguientes 10 años si ellos no resuelven cómo transformar la totalidad de sus empresas para acomodar las nuevas tecnologías"* (IDC Spain, 2019), por tanto, entender cómo los medios sociales ayudan a las empresas a sobrevivir en un mundo en cambio constante y en la creación de valor de negocio es vital en el mundo empresarial. Este trabajo de investigación, pese a las limitaciones detectadas, contribuye de forma novedosa al mundo académico y es de gran interés para la aplicación empresarial.

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Quizás el éxito reside no en la meta, sino en el camino.
El aprender a disfrutar de las pequeñas cosas,
el aprender a disfrutar con cada paso del trayecto.
Vencer miedos y ampliar la zona de confort.

"Lo que imaginas vívidamente,
con ardiente deseo,
sinceramente y con entusiasmo
y actúas en consecuencia…
inevitablemente sucederá"

- Paul J. Meyer